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Essays on Macroprudential and Monetary Policy

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Note to the Reader

The three chapters of this dissertation are self-contained research articles and can be read separately. They are preceded by an introduction which summarizes the research presented in this dissertation. The terms ”paper” or ”article” are used to refer to chapters. The 3 chapters are co-authored.

This thesis and the chapters it contains should not be reported as representing the views of the European Central Bank (ECB) or the Banque de France (BdF). The views expressed are those of the authors.

Contents

List of Figures

List of Tables

Introduction

Monetary policy and macroprudential policy are arguably the two main missions nowadays commonly devoted to central banks. In essence, the former aims at ensuring *consumption* price stability when the latter focuses on *asset* price stability. None of these policies are new. Yet, both the practice of these policies, and the theories underpinning them, have considerably evolved over the last 15 years with the unravelling of the Global Financial Crisis. This PhD thesis contributes to understanding recent developments in both of these fields.

The first two chapters of this thesis contribute to the macroprudential policy literature, through an ex-post assessment of a key macroprudential instrument, the countercyclical capital buffer (Chapter 1), and by examining a potential source of systemic risk, the exchange of credit default swaps, that redistributes credit risk within the financial sector (Chapter 2). Chapter 3 is then devoted to monetary policy through an assessment of the heterogeneous effects of quantitative easing in the euro area.

The 2008 financial crisis was a painful reminder that financial crises can still occur despite strong microprudential supervision. One important reason put forward by Brunnermeier (2009) in his detailed account of the crisis is the natural procyclicality stemming from the "decline in measured risks in a boom and the subsequent rise in measured risks in the subsequent bust". This diagnostic prompted a significant overhaul of financial regulation. While the concept of macroprudential policy was not new,[1] Basel III agreements formally introduced a number of instruments explicitly dedicated to addressing systemic risks. One of the flagship instruments introduced was the *countercyclical capital buffer* (CCyB), aimed at increasing the resilience of the banking sector by forcing banks to accumulate capital during credit booms. The requirement is then released during busts, to support banks' distribution of credit by providing capital headroom. Various studies have recently used the capital requirement releases of the COVID-19 crisis to emphasize how this provides

[1] The usage of the term "macroprudential" is usually dated back to the 1986 Cross report of the Bank of International Settlements.

effective support to bank lending during downturns (Couaillier et al., 2022; Martinez-Miera and Vegas Sánchez, 2021).

The first chapter of this thesis studies the usage of the CCyB in Europe from 2016 to early 2022, to understand how markets react to capital requirements in general, and cyclical capital requirements in particular. The European CCyB framework provides an ideal setup for this. First, national authorities set CCyB requirements in all jurisdictions at a predefined (quarterly) frequency, which provides a large set of comparable announcements. Second, the CCyB rate in a given country applies to all banks of the European Economic Area (EEA) proportionally to the share of that country in their total (relevant) exposure. Consequently, each shock heterogeneously impacts all banks of the EEA, allowing for cross-sectional analyses. We show that CCyB hikes translate in lower Credit Default Swap (CDS) spreads for affected banks, in particular those poorly capitalised. On the other hand, bank valuations do not react. Markets therefore consider that higher countercyclical capital requirements make banks more stable at no material cost for shareholders. We claim that these effects relate to the capital constraint itself, as opposed to the potential signal conveyed on the state of the financial cycle. Indeed, market-wide measures of risk and return such as sovereign CDS spreads and stock indices also do not react to these announcements. To the best of our knowledge, this paper is the first to provide a direct assessment of how markets price capital requirements. Ultimately, our conclusions suggest that macroprudential authorities may have room for a more active usage of the CCyB. The latest developments suggest that this is indeed the case.

Systemic risks often emerge against the backdrop of financial innovations. The widespread development of the CDS market in the run up to the Global Financial Crisis is one of them. Between 2004 and 2008, the size of the CDS market in terms of notional outstanding rose from \$6 tn to as high as \$57 tn (Stulz, 2010). These instruments allow separating funding risk from credit risk, and reallocate these risks to the balance sheets most suited to bear them (Oehmke and Zawadowski, 2015). In practice, CDS were used to *concentrate* credit risk on apparently safe balance sheets like that of the global insurer AIG, which could bear it at a limited regulatory cost, in what appears ex-post to have been akin to regulatory arbitrage (see McDonald and Paulson (2015) for a detailed account of the failure of AIG). Limiting exposure concentration thus became an explicit objective of macroprudential policy.[2]

In Chapter 2, we use a novel dataset of CDS holdings among French investors and upon French reference entities to understand the current determinants of holding CDS and their consequence for the redistribution of risk. Indeed, and despite the events of the financial cri-

[2]See ESRB (2013).

sis, the distributional effects of trading CDS are still underlooked, for at least two reasons. First, CDS are a zero-sum game in aggregate and payoffs are merely transfers inside the financial system. However, recent contributions as Gabaix (2011), Galaasen et al. (2020) or Baena et al. (2022) stress how individual shocks may affect aggregate outcomes and credit supply in particular. As such, individual credit risk exposures may matter for financial stability. Second, studying individual credit risk requires granular data on multiple instruments (loans, bonds, CDS), which are difficult to access and process and have only recently been a focus of researchers. In Europe, granular data on CDS holdings and trades are only available since 2016, thanks to the European Markets Infrastructure Regulation (EMIR) of 2012.[3] In this paper, we put together the three types of exposures, and show that while CDS represent small shares of aggregate credit risk, this share becomes high when it comes to large borrowers. We propose a methodology to disentangle CDS positions between three strategies: hedging, speculation, and arbitrage. Each of these has different consequences for the distribution of credit risk. First, since the majority of CDS purchased do not offset pre-existing debt exposures, their exchange leads to an increase in outstanding exposures at default. Second, we find that hedging and speculation strategies relate to debt exposure concentration. Using a novel instrument for debt concentration to circumvent the fact that investors jointly choose their debt and CDS positions, we show that bank hedgers tend to shed off their most concentrated exposures, while speculators use CDS as complements to build up on their largest pre-existing debt exposures. Finally, we demonstrate that investors' incentives to trade CDS increase with the risk of the reference entity, thereby altering the composition of credit risk outstanding. Overall, our results emphasize the importance of accounting for CDS when analyzing the distribution of large credit risk exposures across investors.

On the monetary policy front, the deflationary risks triggered by the Global Financial Crisis led to massive central bank interventions across the globe through what was then referred to as unconventional monetary policies. Fifteen years later, these policies are now part of the central bank toolkit. In its strategy review statement, while acknowledging that policy rates remained its primary instrument, the European Central Bank recognized it would continue using unconventional instruments such as forward guidance, asset purchases and longer-term refinancing operations, as appropriate.[4] In economies where lower bound constraints on short-term interest rates become occasionally binding, these unconventional

[3]Regulation (EU) No 648/2012 of 4 July 2012 on OTC derivatives, central counterparties and trade repositories.

[4]See `https://www.ecb.europa.eu/home/search/review/html/ecb.strategyreview_monpol_strategy_statement.en.html`.

policies allow to influence longer-term interest rates through a variety of channels. Asset purchase programs have arguably been the most prominent of these policies. Broadly speaking, asset purchases operate by shifting duration, liquidity and credit risk on the central bank's balance sheet, thereby increasing the risk-bearing capacity of private agents who are incentivized to *rebalance* their portfolio towards alternative assets: this is the portfolio rebalancing channel of quantitative easing (Vayanos and Vila, 2021).

The last chapter of this thesis examines how different types of purchases stimulate demand for different types of assets depending on who owns the securities purchased. We leverage on the heterogeneous purchase programs conducted by the Eurosystem from 2014 to 2020 to understand how different types of asset purchases are accommodated. We find that among euro area investors, sovereign securities and covered bonds are primarily purchased from banks, while corporate securities are rather purchased from investment funds. We also show that investors' rebalancing patterns depend on their investment *habitat*. Purchasing securities from banks will spur bank lending, while investment funds may increase their demand for riskier securities if they have the required mandate. Concretely, this means that central banks need to define not only the *quantity* of risk they want to remove from the market, but also identify their potential counterparties. This also implies that asset purchase programs conducted in a monetary union with diverse financial sector structures like the euro area may have heterogeneous effects across countries. If the effects are symmetric, the same arguments would apply in the context of quantitative tightening. Demand is expected to be compressed heterogeneously across geographies and market segments, depending on which securities the central bank chooses to divest.

I now present in more details the chapters composing this PhD thesis.

Chapter 1: How do markets react to tighter bank capital requirements?

The Great Financial Crisis (GFC) highlighted the need for sufficient bank capital, as banking crises and their companion credit crunches are particularly damaging to the real economy. Consequently, the main regulatory response to the GFC consisted in a large increase in bank capital requirements. Their optimal level is however subject to an ongoing debate among academics and policymakers. While higher requirements are associated with more resilience, they can also induce an inefficient reduction in lending (see for instance Van den Heuvel (2008), Repullo and Suarez (2012), Clerc et al. (2015), Mendicino et al.

(2018), Malherbe (2020)). As such, it is key for regulators to strike the appropriate balance between the benefits of more stable banks and the costs of more expensive capital. In this study, we use the institutional setup of the countercyclical capital buffer (CCyB) in the European Economic Area (EEA), in an event-study framework, to assess how financial markets perceive the costs and benefits of higher capital requirements.

The CCyB is a time-varying bank capital requirement introduced in Basel III and adapted in European regulation, that provides two attractive features for such study. To start with, CCyB levels are homogeneous decisions announced quarterly at the national level, and we can precisely identify announcement dates thanks to press releases. This allows for an event study approach. In contrast, changes to the regulatory framework result from years of negotiation, and are largely anticipated. These agreements typically consist in one-off regulatory changes, making it difficult to disentangle the effect of potentially numerous innovations, or to ensure external validity. Since then, the Basel III framework introduced other bank-specific capital requirements, but their computation is often mechanical (e.g. for Global and Other Systemic Banks) and thus easy to anticipate, and/or without a proper communication framework to the markets.[5] Second, the CCyB rate in a given country applies to all banks of the EEA proportionally to the share of that country in their total (relevant) exposures. Consequently, each shock heterogeneously impacts all banks of the EEA, allowing for cross-sectional studies.

CCyB increases could trigger market reactions through two channels. First, they may reveal private information that the national regulator may hold on the state of the economy when setting the rate. The interpretation of such signal is *a priori* ambiguous. Macroprudential authorities typically raise the CCyB when the economy is in good shape, but also when financial risks are building up. We label this the *signalling channel*. The second channel relates to the requirement itself, that tightens the capital constraint, potentially forcing banks to adjust their balance sheet. We label this the *capital channel*. Disentangling both channels is key to appropriately interpret results in terms of costs and benefits.

We proceed in three steps. First, we investigate the impact of CCyB hikes on country-level variables, namely stock indices and sovereign Credit Default Swaps (CDS). We find no significant impact: country-level variables do not systematically react to country-level CCyB increases. This is inconsistent with the *signalling channel* and suggests that any impact is likely to transit through the *capital channel*.

Second, we show that the announcement of a national CCyB hike translates into lower CDS spreads for banks exposed to this country. Markets thus recognize that capital require-

[5] In the European Banking Union, the bank-specific Pillar 2 Guidance is confidential, and the Single Supervisory Mechanism publishes bank-specific Pillar 2 Requirements applying to Significant Institutions only since 2020. See `https://www.bankingsupervision.europa.eu/banking/srep/html/p2r.en.html`.

ments improve bank solvency, consistent with studies highlighting their effect on capital ratios (Alfon et al., 2005) and risk-taking (Behncke, 2022). The effect is more pronounced for banks with lower capital ratios and lower distance to their regulatory capital requirement. Indeed, we find a larger spread decrease of banks below the median of both variables. The interpretation is twofold. Markets anticipate more constrained banks to be more likely to adjust their balance sheet towards higher capital ratios, and higher capital ratios have larger effects on solvency for less capitalised banks.

Finally, we show that CCyB increases are not associated with any stock return regularity. This, in conjunction with the decline in CDS spreads, is again inconsistent with the signalling channel: good economic news lowering CDS spreads should also increase stock value. This confirms the activation of the capital channel, but in a way that has no significant impact on stock prices. Strong stock prices may be beneficial for a regulator, if they reflect the absence of an inefficient reduction in lending, or if they strengthen domestic banks' ability to raise equity or resist unwarranted foreign takeovers. Therefore, we interpret the absence of stock price reaction as evidence that CCyB increases have only muted undesirable effects.

In the process, we also show that CCyB releases had a positive effect on bank and country CDS spreads, and were associated with a drop in stock returns. While these results must be interpreted with caution since most releases happened around the outbreak of the COVID-19 pandemic, a period of heightened volatility, they suggest a signalling channel is at play for CCyB releases. Markets interpret regulators releases as signs of deteriorating prospects for the economy. Releases typically occur in periods of higher volatility, where information released by the regulator may have increased relevance.

From a policy perspective, our results suggest that macroprudential authorities have room for a more active use of the CCyB to increase bank resilience, while not adversely affecting bank valuations.

Chapter 2: CDS Trading Strategies and Credit Risk Reallocation

Credit Default Swaps (CDS) are controversial financial instruments - "weapons of mass destruction" according to W. Buffet. On the one hand, CDS might improve the allocation of credit risk allowing illiquid but optimistic investors to gain credit risk exposure (Oehmke and Zawadowski, 2015). On the other hand, CDS reduce monitoring incentives because of the empty creditor problem (Bolton and Oehmke, 2011), and may even facilitate agents' coordination to "bad" equilibria (Bruneau et al., 2014). These contributions primarily focus

on how CDS affect asset prices or the risk of referenced entities. However, they remain silent on the distributional consequences of CDS on investor-level risk for at least two reasons.

First, CDS are a zero-sum game in aggregate and payoffs are merely transfers within the financial system. However, recent contributions as Gabaix (2011), Galaasen et al. (2020) or Baena et al. (2022) stress how individual shocks may affect aggregate outcomes and credit supply in particular. As such, individual credit risk exposures may matter for financial stability.[6] Second, studying the distribution of credit risk requires granular data on multiple instruments (loans, bonds, and CDS), which are difficult to access and process and have only recently been a focus of researchers.

Using granular quarterly data on both debt and CDS exposures of French investors to non-financial corporations (NFC) and euro area banks and investment funds to French NFCs from 2016$Q1$ to 2021$Q4$, we provide new answers to how CDS reallocate credit risk across investors. This occurs in three manners.

First, CDS trading may increase the *total* outstanding amount of credit risk exposures, or exposures at default (EAD), to the extent that not all CDS purchases offset preexisting debt exposures. Second, CDS trading may alter the *concentration* of exposures across investors. Third, CDS trading may affect the *composition* of outstanding credit risk.

To guide our investigation, we first contribute to the literature by disentangling CDS positions along three trading motives, each with different consequences for credit risk reallocation: arbitrage, hedging, and speculation. To do so, we leverage on our granular dataset at the investor-reference entity-quarter level to identify whether debt and CDS exposures offset or amplify each other, whether the debt is a bond or a loan, and whether positions are acquired simultaneously or successively.

Arbitrageurs take offsetting positions in CDS and debt to benefit from relative price discrepancies. We identify them as offsetting positions where debt takes only the form of bonds, and where both the debt and the CDS positions are simultaneously acquired. This strategy is anecdotal and represents 2% of CDS purchasers, and a mere 0.03% of CDS sellers.

Hedgers use CDS as an insurance product to downsize corresponding credit risk exposures, either in reaction to shocks, or to maintain lending relationships. We identify them as offsetting positions where either the CDS is purchased after the debt position, or both are jointly acquired and the debt is at least partially a loan. Hedging represents 19% of CDS purchases, and almost exclusively corresponds to hedging in response to shocks. Other types

[6] Studying credit risk at the individual level also finds support in bank capital regulation, which constrains the use of CDS for hedging purposes to debt instruments on the same reference entity. Article 213 of the EU Capital Requirements Regulation (CRR) stipulates that "credit protection deriving from a guarantee or credit derivative shall qualify as eligible unfunded credit protection where all the following conditions are met: (a) the credit protection is direct [...]".

of offsetting CDS purchases add to 6% of net positions.

Finally, speculators use CDS as an alternative venue to amplify debt exposures or to gain a credit risk exposure without holding the underlying debt. Speculation represents 73% of CDS purchases, while virtually all CDS sellers are speculators. Purchasing CDS, may in particular be the main venue to get short credit risk positions, because short-selling debt may involve costly frictions.[7] Indeed, we find that 95% of short credit risk exposures trade through CDS.

As CDS selling seldom corresponds to hedging or arbitrage, almost every CDS sold will increase the selling investors' EAD. Whether the transaction also increases total outstanding EAD then depends on the share of short speculators among CDS purchasers. In our dataset, accounting for CDS leads to an increase in EAD against CDS-referenced entities of 10 to 15%.

In a model of risk-sharing with fixed costs, Atkeson et al. (2015) predict as expected that hedgers offset their largest debt exposures. By contrast, theory yields conflicting predictions on whether CDS should be used as a substitute or a complement to debt by speculators. They could substitute debt with CDS following a risk-sharing motive. Additionally, CDS have lower trading costs than debt in Oehmke and Zawadowski (2015) where investors optimally choose their preferred instrument depending on their liquidity profile. However, according to Che and Sethi (2014), speculators take advantage of CDS lower margin requirements to leverage their beliefs and double up their existing debt exposures.

There are two challenges in identifying the effect of exposure concentration on CDS trading. First, becoming a CDS reference may affect the reference entity's behavior with consequences on exposure concentration and riskiness. Empirical contributions on the effect of CDS on reference entity debt tend to show that CDS trading induces firms to issue more debt at lower rates (Hirtle, 2009; Saretto and Tookes, 2013), and ultimately become riskier (Subrahmanyam et al., 2014). We restrict our analysis to reference entities on which CDS are traded at least once over the sample, so that they all have a priori similar incentives to increase leverage.

The second and main challenge with relating CDS trading to debt concentration is that both positions may be jointly determined. Investors may be taking larger debt exposures knowing they can partly shed them off in the CDS market, and smaller debt exposures if they can sell CDS on the same reference entity. To circumvent this issue, we instrument each investor-reference entity debt exposure by the share of the reference entity's gross debt in the universe if reference entities ever held by the investor. The instrument's relevance

[7] Short-selling debt requires locating securities lenders and managing the risk of not finding securities sellers upon termination (Duffie et al., 2002; Nashikkar et al., 2011).

requires that investors partially allocate their debt holdings proportionally across reference entities within their investment habitat.

Addressing these two identification challenges is one of the key innovations of this paper, which thus improves on the standard theoretical (Atkeson et al., 2015) and empirical (Oehmke and Zawadowski, 2017; Jiang et al., 2021) tradition that assumes debt exposures as given when looking at the effects of CDS.[8]

As expected, banks and dealers use CDS to hedge their most concentrated exposures, although concentration does not seem to matter for fund hedgers. This could relate to stronger regulation on banks' exposure concentration.[9] The effects are economically important: for every additional percentage point of debt concentration, the probability of hedging that exposure increases by almost 31pp for banks, and by as much as 113pp for dealers (to be compared with median debt exposure concentrations of respectively 0.11pp and 0.07pp among potential hedgers).

Furthermore, our results corroborate Che and Sethi (2014) view for banks and investment funds on speculators. Conditional on holding some debt, investors sell more CDS if the reference entity debt accounts for a larger proportion of their debt portfolio. The absence of results on dealers is consistent with their role as intermediaries, their positions mirroring to a large extent the trading strategies of their counterparts. As for hedging, the effects are economically significant: the probability of selling CDS on top of existing debt exposures increases by 6pp for funds and as much as 103pp for banks for every additional percentage point of exposure concentration (to be compared with median debt exposure concentrations of respectively 0.5pp and 0.03pp among potential long speculators).

By definition, naked speculators trade CDS on exposures for which they have no underlying debt. However, we also find that banks and dealers tend to sell more CDS for country-rating exposures they already hold most of, again validating the considerations of Che and Sethi (2014).

In the last part of the paper, we ask whether CDS change the risk composition of exposures outstanding. There are at least four reasons why investors' incentives to trade CDS (relative to debt) may increase with reference entity risk. Disagreement on reference entity risk (Oehmke and Zawadowski, 2015), or incentives for hedging Atkeson et al. (2015) could both be higher for riskier firms. CDS may also require less initial margins than similar leveraged positions in the debt market, an advantage that grows with reference risk (Darst and Refayet, 2018). Finally, benefits from trade opacity could increase with reference entity

[8]This usually rests on the assumption that debt is less liquid than CDS.

[9]For instance, Article 394 of CRR requires banks to report all exposures exceeding 10% of their eligible capital, while Article 395 imposes a hard limit to exposure concentration of 25% of eligible capital.

riskiness (Jiang et al., 2021).

As for concentration, these analyzes may be subject to endogeneity as credit risk positions in debt and CDS are jointly determined. Investors trading CDS may reduce holdings of riskier debt securities knowing that CDS are relatively attractive for these risk levels. We address this concern by comparing the riskiness of debt portfolios between investors that trade CDS and similar investors that do not, and do not find evidence that investors change their behavior on the debt market upon entering the CDS market.

Within investor, the probability to trade CDS increases with the reference entity's risk, as measured by its CDS spread, for all strategies and all sectors. These results hold controlling for bond and CDS liquidity. We also find evidence that banks, dealers, and to some extent investment funds, use CDS for rating arbitrage i.e., they trade more CDS on reference entities with higher spreads conditional on a credit rating. This behavior may be driven by communication or regulatory incentives (Becker and Ivashina, 2015).[10]

Overall, CDS appear to have an ambiguous effect on the distribution of credit risk across investors, although this paper does not offer a normative framework. Investors might use CDS to hedge their most concentrated exposures. At the same time, the introduction of CDS increases the amount of exposures at default, allows investors to double up on their beliefs, and tilts the composition of credit risk outstanding towards riskier reference entities.

Chapter 3: Habitat Sweet Habitat: the Heterogeneous Effects of Eurosystem Asset Purchase Programs

The growing variety of asset purchase programs and the increasing flexibility that central banks have in implementing them,[11] suggest that all asset purchases are not equivalent. In particular, the portfolio rebalancing channel may operate differently depending on who initially owns the securities targeted and eventually purchased. Intuitively, purchasing securities owned by banks may support bank lending, while purchasing securities owned by investment funds may instead increase their demand for non-purchased and potentially riskier securities.

One of the most widely used theoretical framework to understand portfolio rebalancing is preferred habitat (PH) theory, pioneered by Tobin (1965). As Haruhiko Kuroda, former Governor of the Bank of Japan, put it:

[10] Article 122 of CRR prescribes rating-dependent risk weights for calculating capital requirements in the standard approach.

[11] For example, the Eurosystem decided to allow flexible reinvestment of its PEPP portfolio reflecting a willingness to be able to support prices in specific segments of the market. See: `https://www.ecb.europa.eu/press/pr/date/2021/html/ecb.mp211216~1b6d3a1fd8.en.html`.

> Whether central banks' large-scale asset purchases succeed in reducing term premiums hinges upon whether the preferred habitat hypothesis holds.

In that framework, central bank asset purchases operate by reducing the existing and expected amount of duration, liquidity and credit risk in the economy, thereby reducing the market price of risk (Vayanos and Vila, 2021; Altavilla et al., 2021). Accordingly, the type of assets purchased matters to the extent that each security bears a different amount of risk.

PH theory predicts that these heterogeneous effects may also depend on who initially owns the securities purchased. In the framework, demand for assets is segmented. *Arbitrageurs* have mean-variance preferences and ensure a no-arbitrage condition prevails across securities. Conversely, *preferred habitat* investors have price-sensitive demand over specific asset classes. This gives rise to two additional channels. First, asset purchases have local price effects. Reducing the supply of assets from PH investors' habitat increases the price of those assets above what would be predicted by the no-arbitrage condition of arbitrageurs only. For example, investment funds with a mandate for investing in euro area (EA) government debt securities may be reluctant to sell those by lack of alternative investment opportunities. Second, the segmentation of investors opens up the possibility of rebalancing across sectors. At constant asset supply, yield curve changes may affect relative asset demand. In the presence of balance sheet constraints, valuation gains may also disproportionately affect certain sectors and increase their demand for assets (Albertazzi et al., 2020). But perhaps more importantly, changing the composition of asset supply by substituting debt securities with central bank reserves could trigger rebalancing as asset sellers recompose their optimal portfolio. As stated upon the announcement of quantitative easing by the European Central Bank (ECB):[12]

> The ECB will buy bonds issued by euro area central governments, agencies and European institutions in the secondary market against central bank money, which the institutions that sold the securities can use to buy other assets and extend credit to the real economy.

This type of rebalancing is further enhanced when the supply of assets increases - either mechanically when the central bank purchases securities from non-reserve holding institutions (Christensen and Krogstrup, 2016), or indirectly as a result of increased issuance (see for instance Abidi and Miquel-Flores (2018) or Todorov (2020) who show how the Corporate Sector Purchase Program (CSPP) stimulated corporate bond issuance). We dub it the "liquidity-driven portfolio rebalancing channel", and it will be the focus of this paper.

[12]See: `https://www.ecb.europa.eu/press/pr/date/2015/html/pr150122_1.en.html`.

We show that portfolio rebalancing differs depending on who owns the securities purchased. To address this question, one would ideally examine how two investors with different habitats rebalance upon selling the same security to the central bank. However, purchases of all kind of securities are simultaneous and it seems difficult to disentangle the effect of different types of sales. Therefore, we proceed in two steps, leveraging on the specific features of Quantitative Easing (QE) in the EA. First, we identify the counterparts to Eurosystem purchases and estimate their relative elasticities to purchases depending on the nature of the security purchased. Second, we estimate how each type of investor rebalances upon selling any security to the Eurosystem.

The first part of the paper leverages on the diversity of asset purchase programs implemented in the EA to identify the counterparts to Eurosystem purchases depending on the type of security purchased. To do so, we put together a rich database of security-level holdings by investment sector, jointly with security-level Eurosystem asset purchases from four different asset purchase programs over 2014Q3-2020Q4: the third wave of the Covered Bond Asset Purchase Programs (CBPP3), the Public Sector Purchase Program (PSPP), the Corporate Sector Purchase Program (CSPP), and the Pandemic Emergency Purchase Program (PEPP). We examine heterogeneous purchases across two dimensions: by asset class - thereby assessing the impact of the different purchase programs, and by maturity. We compare holding variations in securities purchased to that of similar non-purchased securities, for the three main EA holding sectors: banks, investment funds (IF), and insurance companies and pension funds (ICPF). Identifying who sells greater shares of their holdings to the Eurosystem controlling for sector-time demand for eligible securities allows us to rank the elasticities of different sectors for each type of asset purchased. To the best of our knowledge, we are the first to explicitly estimate relative elasticities to different types of purchases, thanks to having a unique access to security-level purchase data for four different programs.

We find that banks are the most elastic EA investors for sovereign and covered bonds, while they are equally elastic to IF for corporate bonds. Due to their large market share in the former, banks end up being the largest EA sellers in volumes to CBPP3, PSPP and PEPP, while IF are the largest sellers to CSPP. ICPF appear equally elastic to IF for sovereign and covered bonds, and less elastic than both IF and banks for corporate bonds.

Across maturities, differences between sectors widen as maturity increases, and banks appear to be the sole sellers of securities of residual maturity above 15 years. The elasticity (relative to other sectors) of ICPF declines as maturity increases, while that of IF peaks for intermediate maturities. One reason for this heterogeneity is again that different types of investors have different maturity habitats. Alternatively, asset purchases may alter investors' maturity preferences. We use investor-level data to disentangle both effects, assuming each

investor's preferred maturity corresponds to its mean maturity holding prior to the start of QE. IFs' behavior indeed resembles that of preferred habitat investors who are more elastic to purchases of securities further away from their habitat. This is consistent with IF being tied to a stricter form of habitat - investment mandates. On the other hand, ICPFs appear to tilt their portfolios towards higher maturities, pointing to a reach for maturity behavior.

In the second part of the paper, we estimate how different types of investors rebalance their portfolio upon selling to the Eurosystem. This amounts to focusing on the *liquidity-driven portfolio rebalancing channel* since those investors selling to the Eurosystem are the ones experiencing the substitution of debt securities by liquid assets.[13] While portfolio rebalancing may also have other causes like stealth recapitalization induced by valuation gains, our interest is to know whether who owns the securities purchased matters. Investors owning the securities purchased are directly affected by the liquidity-driven portfolio rebalancing channel, while stealth recapitalization effects depend on asset price movements which can occur even absent any asset purchase.

To proceed, we build a direct measure of asset sales by investor, which we relate to growth in holdings at the investor-security level. While investor-level asset sales are not directly observable, we infer that amount from variations in investor holdings of purchased securities at quarterly frequency. Our identification relies on three key features.

First, estimating asset sales is subject to both omitted variables and reverse causality biases. Regarding the former, other shocks than QE may drive a correlation between our measure of asset sales and shifts in demand. For instance, an investment fund experiencing outflows perhaps needs to reduce its holdings, including those of assets simultaneously purchased by the Eurosystem, which would look like QE led this fund to reduce its holdings. Turning to reverse causality, investors looking to downsize could tend to promote their assets to the Eurosystem, which may in turn disproportionately buy from distressed investors.[14] To circumvent this endogeneity of asset sales at the investor-level, we instrument asset sales by the investor's exposure to assets eligible for purchase in the period immediately preceding, as in Rodnyansky and Darmouni (2017) or Koetter (2020).

Another concern is that investors exposed to Eurosystem purchases are disproportionately exposed to increases in asset supply from issuers. Here, we leverage on our granular database to implement ISIN-quarter fixed effects that absorb any asset supply shock, in the spirit of Khwaja and Mian (2008).

Finally, a more generic concern is that exposure to central bank purchases may be corre-

[13]Central bank reserves in the case of banks, or bank deposits in the case of non-banks.

[14]Eurosystem direct counterparts are always dealer banks, but ultimate sellers of securities may be from any sector.

lated with other investor-level shocks that may affect demand for assets. Therefore, for each sector, we control for a (different) number of balance sheet characteristics that could indeed affect asset demand.

Different rebalancing patterns between sectors arise. Selling ICPF somewhat increase demand for non-EA debt securities, although our instrument is weaker in this analysis since there is more limited variability in ICPF asset sales. Among investment funds, investment mandates appear to dictate the extent of rebalancing. Debt funds tend to substitute the securities sold with similar types of debt securities. On the other hand, diversified funds also tend to increase demand for equities, as well as for non-EA debt securities. Finally, banks do not appear to change their demand for securities. Instead, we find evidence that banks selling to the Eurosystem increase lending over 2019 and 2020. This is consistent with papers finding that excess reserves have a positive impact on lending (Rodnyansky and Darmouni, 2017; Koetter, 2020; Kandrac and Schlusche, 2021; Christensen and Krogstrup, 2019).

Purchasing from different types of investors does not emulate demand for assets in an homogeneous manner. This has important implications for the design of central bank asset purchase programs. Central banks not only need to decide the amount of risk to remove from the market but also assess which counterparts to purchase from. Purchasing assets belonging primarily to commercial banks (as during CBPP3 or PSPP, or with purchases longer-term securities) enhances bank lending. On the other hand, purchasing primarily from investment funds (as during CSPP, or with purchases of shorter-term securities) amplifies rebalancing towards riskier assets if selling funds have flexible investment mandates.

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Chapter 1

How do markets react to tighter bank capital requirements?

This chapter is based on a paper co-authored with Cyril Couaillier (ECB) and published in the Journal of Banking and Finance in June 2023.

Abstract

We use hikes in the countercyclical capital buffer [CCyB] to measure how markets react to tighter bank capital requirements. Our identification strategy relies on two unique features of the CCyB institutional framework in Europe. First, all national authorities make quarterly announcements of CCyB rates. Second, these hikes affect all European banks proportionally to their exposure to the country of activation. We show that CCyB hikes translate in lower CDS spreads for affected banks, in particular those poorly capitalised. On the other hand, bank valuations do not react. Markets therefore consider that higher countercyclical capital requirements make banks more stable at no material cost for shareholders. We claim that these effects relate to the capital constraint itself, as opposed to the potential signal conveyed on the state of the financial cycle.

1. Introduction

The Great Financial Crisis (GFC) highlighted the need for sufficient bank capital, as banking crises and their companion credit crunches are particularly damaging to the real economy. Consequently, the main regulatory response to the GFC consisted in a large increase in bank capital requirements. Their optimal level is however subject to an ongoing debate among academics and policymakers. While higher requirements are associated with more resilience, they can also induce an inefficient reduction in lending (see for instance Van den Heuvel (2008), Repullo and Suarez (2012), Clerc et al. (2015), Mendicino et al. (2018), Malherbe (2020)). As such, it is key for regulators to strike the appropriate balance between the benefits of more stable banks and the costs of more expensive capital. In

this study, we use the institutional setup of the countercyclical capital buffer (CCyB) in the European Economic Area (EEA), in an event-study framework, to assess how financial markets perceive the costs and benefits of higher capital requirements.

The CCyB is a time-varying bank capital requirement introduced in Basel III and adapted in European regulation, that provides two attractive features for such study. To start with, CCyB levels are homogeneous decisions announced quarterly at the national level, and we can precisely identify announcement dates thanks to press releases. This allows for an event study approach. If announcements were partially anticipated, our estimates would simply be conservative. In contrast, changes to the regulatory framework result from years of negotiation, and are largely anticipated. These agreements typically consist in one-off regulatory changes, making it difficult to disentangle the effect of potentially numerous innovations, or to ensure external validity. Since then, the Basel III framework introduced other bank-specific capital requirements, but their computation is often mechanical (e.g. for Global and Other Systemic Banks) and thus easy to anticipate, and/or without a proper communication framework to the markets.[1] Second, the CCyB rate in a given country applies to all banks of the EEA proportionally to the share of that country in their total (relevant) exposures. Consequently, each shock heterogeneously impacts all banks of the EEA, allowing for cross-sectional studies.

CCyB increases could trigger market reactions through two channels. First, they may reveal private information that the national regulator may hold on the state of the economy when setting the rate. The interpretation of such signal is *a priori* ambiguous. Macroprudential authorities typically raise the CCyB when the economy is in good shape, but also when financial risks are building up. We label this the *signalling channel.* The second channel relates to the requirement itself, that tightens the capital constraint, potentially forcing banks to adjust their balance sheet. We label this the *capital channel.* Disentangling both channels is key to appropriately interpret results in terms of costs and benefits.

We proceed in three steps.

First, we investigate the impact of CCyB hikes on country-level variables, namely stock indices and sovereign CDS. We find no significant impact: country-level variables do not systematically react to country-level CCyB increases. This is inconsistent with the *signalling channel* and suggests that any impact is likely to transit through the *capital channel.*

Second, we show that the announcement of a national CCyB hike translates into lower CDS spreads for banks exposed to this country. Markets thus recognize that capital require-

[1] In the European Banking Union, the bank-specific Pillar 2 Guidance is confidential, and the Single Supervisory Mechanism publishes bank-specific Pillar 2 Requirements applying to Significant Institutions only since 2020. See `https://www.bankingsupervision.europa.eu/banking/srep/html/p2r.en.html`.

ments improve bank solvency, consistent with studies highlighting their effect on capital ratios (Alfon et al. (2005)) and risk-taking (Behncke (2022)). The effect is more pronounced for banks with lower capital ratios and lower distance to their regulatory capital requirement. Indeed, we find a larger spread decrease of banks below the median of both variables. The interpretation is twofold. Markets anticipate more constrained banks to be more likely to adjust their balance sheet towards higher capital ratios, and higher capital ratios have larger effects on solvency for less capitalised banks.

Finally, we show that CCyB increases are not associated with any stock return regularity. This, in conjunction with the decline in CDS spreads, is again inconsistent with the *signalling channel*: good economic news lowering CDS spreads should also increase stock value. This confirms the activation of the *capital channel*, but in a way that has no significant impact on stock prices. Strong stock prices may be beneficial for a regulator, if they reflect the absence of an inefficient reduction in lending, or if they strengthen domestic banks' ability to raise equity or resist unwarranted foreign takeovers. The absence of negative stock price reaction would also suggest that the CCyB announcement is well understood by the markets, an important attention point for prudential authorities. Therefore, we interpret the absence of stock price reaction as evidence that CCyB increases have only muted undesirable effects.

In the process, we also show that CCyB releases had a positive effect on bank and country CDS spreads, and were associated with a drop in stock returns. While these results must be interpreted with caution since most releases happened in the specific period of the outbreak of the COVID-19 pandemic, they suggest a signalling channel is at play for CCyB releases. Markets interpret regulators releases as signs of deteriorating prospects for the economy.

From a policy perspective, our results suggest that macroprudential authorities have room for a more active use of the CCyB to increase bank resilience, while not adversely affecting bank valuations.

Our paper stands at the crossroads of two strands of the literature.

A first strand of the literature investigates the impact of countercyclical capital requirements. Jimenez et al. (2017) investigate the impact of the Spanish dynamic provisioning, an instrument conceptually similar to the CCyB and implemented before the GFC. Chen et al. (2019) assess the impact of the release of a countercyclical capital add-on on Slovenian banks during the GFC. Both papers find that such countercyclical capital tools supported credit supply during the crisis. Several papers also studied the effect of the Swiss sectoral CCyB on real estate exposures, and showed how it translated in a reallocation of lending (Auer et al. (2022)), an increase in mortgage rates (Basten (2020)) or a reduction in loan-to-value ratios (Behncke (2022)). A large literature also provides models to investigate ex-ante the

expected impact of the CCyB and calibrate the optimal level (among other, Clerc et al. (2015); Mendicino et al. (2018); Malherbe (2020)). Our paper brings a complementary view by measuring market participants perception, and investigating how they value potential adjustments.

A second strand of the literature deals with the impact of capital requirements on market valuations. Stress testing exercises have been used to measure the impact of capital requirements. In these exercises, regulators simulate episodes of financial stress to identify under-capitalized banks, whose capital requirements may subsequently be tightened. The 2011-12 European Banking Authority (hereafter EBA) stress tests (Mésonnier and Monks (2015)), as well as the stress tests preceding the launch of the Banking Union in Europe in 2013-14 (Carboni et al. (2017)) entailed negative abnormal stock returns for the weakest banks. Moreover, Mésonnier and Monks (2015) showed that banks with higher capital shortfalls experienced CDS spread increases following announcements: stress tests revealed the fragility of some banks to market participants. Indeed, stress tests differ widely in their setups and convey lots of private information at the bank-level (Morgan et al. (2014), Petrella and Resti (2013)), since one of their objective is to increase market transparency. Therefore event studies of specific stress tests do not capture the mere effect of capital requirements. Conversely, the CCyB setup provides a stable regulatory environment to study capital requirement hikes across multiple announcements. Another series of papers investigates the differentiated impact of regulatory-induced and managers-induced bank capital issuance. Using Japanese data, Cornett and Tehranian (1994) show that regulatory-induced capital issuance trigger weaker negative abnormal returns that voluntary issuance. This is consistent with the latter conveying more private information on possible stock overpricing. By the same token, Elyasiani et al. (2014) show that investors positively valued announcements of Troubled Asset Relief Program capital injections in the US, while they generally negatively receive private seasoned equity offerings. Our results are consistent with these findings: regulatory-driven capital ratio increases do not entail any drop in stock returns. Finally, some papers focus on the impact of actual leverage on CDS spreads and show that lower leverage is associated with lower CDS spreads (Benbouzid et al. (2017), Annaert et al. (2013)).

To the best of our knowledge, our setup allows us to make the first direct empirical estimation of the impact of capital requirement announcements on financial markets.

The rest of the paper is organized as follow. Section 2 presents the European CCyB framework, Section 3 the empirical strategy and Section 4 the data. Results are housed in Section 5. Section 6 concludes.

2. The CCyB framework

The CCyB is a time-varying bank capital requirement introduced with Basel III agreements. It is designed to tackle the procyclicality of bank credit (see for instance Dewatripont and Tirole (2012), Martinez-Miera and Suarez (2014), Davydiuk (2017), Mendicino et al. (2018), Malherbe (2020) for theoretical rationales for countercyclical capital requirements). As explained by the European Systemic Risk Board (ESRB (2014)):

> The countercyclical capital buffer is designed to help counter procyclicality in the financial system. Capital should be accumulated when cyclical systemic risk is increasing, creating buffers that increase the resilience of the banking sector during periods of stress when losses materialise. This will help maintain the supply of credit and dampen the downswing of the financial cycle. The countercyclical capital buffer can also help dampen excessive credit growth during the upswing of the financial cycle.

The CCyB has thus two, ranked, objectives: first, improving the resilience of the banking system during financial crises; second, leaning against excessive growth of credit in the upward phase of the financial cycle. Its mechanism is the following. In a boom, authorities raise the CCyB. In reaction, bank managers adjust balance sheet structure, trading off the costs of lower leverage with those of breaching the constraint if capital is too low.[2] This adjustment can take place through three different channels: an increase in equity levels through equity issuance or retained earnings, a decrease in asset size, or a de-risking on the asset side to decrease risk-weights. Then, when an aggregate negative shock occurs (typically a financial crisis), the authority releases the CCyB.[3] This allows banks to use the freed capital to absorb losses and bear an increase in their portfolio risk-weights, without having to cut on lending or their solvency being questioned. Ultimately, this mitigates the risk of a credit crunch.

The CCyB is expressed in percentage of Risk-Weighted Assets (RWA) and capital is to be raised in the form of common equity tier 1 capital (CET1).[4] In the EEA,[5] each bank

[2]The CCyB enters the so-called *Combined Buffer Requirement* (CBR). Breaching it triggers restrictions in capital payouts (dividends, share buybacks, bonuses) and requires the bank to present a *Capital Conservation Plan* to supervisors. This also means that CCyB hikes may have a smaller impact on capital ratios than Pillar 1 or Pillar 2 requirements which directly constrain bank balance sheets.

[3]Therefore, the pass-through of capital requirements is expected to be smaller for CCyB hikes than for usual permanent capital requirements. Indeed, breaching the CCyB should only occur for negative idiosyncratic shocks. See details in B.

[4]CET1 is the purest form of capital consisting mainly of retained earnings and issued capital.

[5]The CCyB was included in the European regulatory financial framework via the EEA relevant *Capital Requirements Directive IV*, and specifically Articles 130, 135, 136, 140 of Directive 2013/36/EU of the Eu-

must compute a specific CCyB rate, defined as the average of country-level rates fixed by national authorities, weighted by banks capital requirement due to *relevant* risk-weighted exposure to each country (see details in B). Bank-specific CCyB rates can thus be expressed as follows:

$$CCyB_{b,t} = \sum_{c=1}^{N} \left\{ CCyB_{c,t} * \frac{Requirement_{b,c,t}^{RWA\,relevant}}{\sum_{k=1}^{N} Requirement_{b,k,t}^{RWA\,relevant}} \right\}, \tag{1.1}$$

with b the bank, t the date, and c in $1, ..., N$ the countries. $CCyB_{c,t}$ is the CCyB rate applying to banks in the EEA for their exposures in country c.[6] As a result, each country-level CCyB announcement automatically results in an heterogeneous effect on all banks of the EEA, proportional to their relevant exposures to the activating country.

In the European framework, the CCyB is set on a quarterly basis by national authorities. Upon decision, they must publish the rate along with an explanation for their decision. This feature allows us to identify exact announcement days by relevant authorities.[7] They must follow the principle of *guided discretion*: they are free to set the CCyB rate, but must rely on quantitative indicators to ground their decision, in particular on the *buffer guide* - the deviation of the credit-to-GDP ratio from its long-term trend.

The CCyB framework was meant to enter into force on January 1st, 2016. Nevertheless, Norway, Sweden, and Czech Republic opted for early implementation and started using the CCyB back in 2013.

3. Empirical approach

Our empirical approach consists in studying the impact of CCyB shocks on country-level and bank-level CDS spreads and stock prices. We follow standard methods for event studies (see for instance MacKinlay (1997)). We study events occurring during defined event windows - in our baseline the (0,2) window - considering the event takes place on the day of the announcement and in the two following days. In case investors take time to digest new information, or if announcements are made at the end of business days, this allows us to fully capture market reactions. Our result remain valid in alternative event specifications.

ropean Parliament and of the Council of 26 June 2013: `https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:32013L0036&from=FR` (CRD IV), adopted in 2013 and then transposed into national laws. CRD IV formalizes the capital regulations introduced in Basel III agreements, among which the CCyB.

[6] See B for details on this formula.

[7] The CCyB is set nationally on a quarterly basis by so-called *designated* authorities. In some cases, a distinct *macroprudential authority* is in charge of making CCyB recommendations to the *designated authority*. In the latter case, we take *macroprudential authorities* announcements as the relevant information-producing shock.

We specify our residuals covariance matrix as in Driscoll and Kraay (1998) so that our estimates are robust to heteroskedasticity and serial cross-correlation of errors, a common feature in financial markets.

We define CCyB shocks as changes in CCyB level. Ideally, one would define shocks as unexpected CCyB changes, in which case the announcement of a constant CCyB could also come as a surprise. However, there are no financial instruments at our disposal to run such a study - as for instance Fed Funds Rate futures in monetary policy. Nevertheless, several arguments support our approach. First, although in law the buffer guide could be a measure of market expectations, in practice CCyB rates implemented substantially differ from it due to the use of guided discretion, making anticipation difficult.[8] Second, anticipation of hikes would only produce a conservative bias in our estimates. Third, in Appendix 1.12, we verify that markets do not react to announcements of constant CCyB rates. Conversely, the systematic reaction of markets upon CCyB changes validates the assumption that these come as (at least partial) surprises.

We follow Andres et al. (2021) in measuring abnormal CDS spread changes in relative rather than absolute terms. We also follow their guidance in specifying normal CDS spread growth with a 4-factor model F_t including: (i) 10-year AAA European sovereign instantaneous forward rate to measure the level of the risk-free yield curve; (ii) 10-year AAA European sovereign yield to measure the slope of the risk-free yield curve; (iii) VSTOXX to measure equity-implied volatility; (iv) the STOXX600 financials index to measure relevant stock market performance. All 4 factors are expressed in daily growth rates. We also analyze how stock indices respond to CCyB changes, and specify normal stock index returns as a linear function the European stock index daily return produced by MSCI. We estimate the following regressions:

$$\Delta CDS_{dt} = \beta * \Delta CCyB_{dt} + \gamma_d * \Delta F_t + \nu_d + \epsilon_{dt}, \tag{1.2}$$
$$\Delta Stock_{dt} = \beta * \Delta CCyB_{dt} + \gamma_d * \Delta StockIndex_{et} + \nu_d + \epsilon_{dt}. \tag{1.3}$$

where d designates either a country c or a bank b, ν_d the corresponding fixed effects, $\Delta CCyB_{dt}$ the value of the CCyB hike (country or bank-specific). The endogenous variables are alternatively the daily variation in 5-year domestic (bank) CDS spreads, and the daily return of the domestic (bank) stock index. $\Delta StockIndex_{et}$ designates the daily return of the stock index of reference: MSCI Europe for country regressions, the main domestic stock index for bank regressions.

Subsequently, we investigate whether the impact of CCyB hikes depends on banks char-

[8] See for instance ESRB (2020): "When looking at developments in the Basel credit-to-GDP gap across Member States, a relatively high degree of heterogeneity can be observed in their setting of CCyB rates."

acteristics. For this purpose, we interact CCyB hikes with a dummy capturing whether the bank belongs to the higher or lower half of the sample on given characteristics:

$$\Delta CDS_{bt} = \beta * \Delta CCyB_{bt} * D_{bt} + \lambda * \Delta CCyB_{bt} * (1 - D_{bt}) + \gamma_b * \Delta F_t + \nu_b + \epsilon_{bt}, \tag{1.4}$$

$$\Delta Stock_{bt} = \beta * \Delta CCyB_{bt} * D_{bt} + \lambda * \Delta CCyB_{bt} * (1 - D_{bt}) + \gamma_b * \Delta StockIndex_{et} + \nu_b + \epsilon_{bt}, \tag{1.5}$$

with D_{bt} capturing in turn bank capitalization (CET1 ratio), or distance to the banks' regulatory capital requirement (the difference between the banks' CET1 ratio and its Overall Capital Requirement (OCR)- see B).

4. Data

We proceed in four steps to build bank-level CCyB shocks.

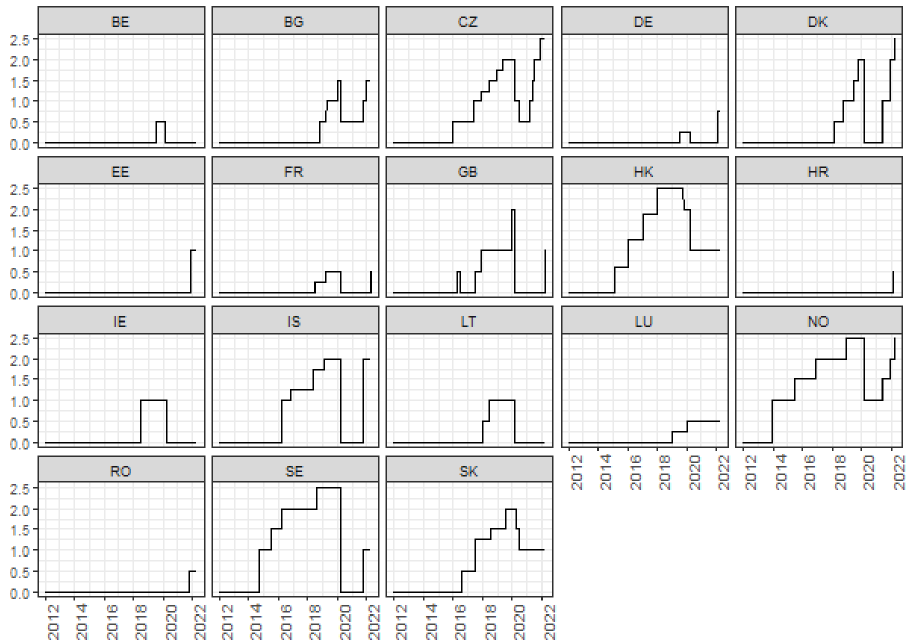
First, we collect all quarterly CCyB decisions by national authorities gathered by the European Systemic Risk Board from 2013 to March 2022.[9] Although the framework became operational in 2016, some countries opted for early activations (Norway, Sweden, Czech Republic). We add to this list the decisions taken by the Hong-Kong authority, starting in 2015. In the period of study, 18 countries activated the CCyB (Figure 1.1).

Interestingly, banks are better capitalised in countries using the CCyB than in countries that never activated it (see Figure 1.2). Designated authorities may be keener to increase the CCyB if domestic banks exhibit large capital ratios, expecting banks to have enough capital to easily absorb the shock. Moreover, banks may partially anticipate future CCyB hikes in countries having already activated it, and thus preemptively increase their capital ratios. If anything, those two explanations would make our estimates conservative, as better capitalised banks should have lower adjustment needs. Empirically, we confirm that the CDS of better capitalised banks react less to CCyB announcements.

Second, we collect the exact date of CCyB announcements on national authorities' websites, taking into account potential differences in national frameworks. We choose the relevant announcement day to be the day of the first announcement of the increase, may it be a recommendation by the macroprudential authority, or a decision by the designated authority. When national authorities use forward guidance, we exclude both the initial guidance and the subsequent official announcement. We finally exclude the Norwegian activation of December 2013, since that increase was to become effective 1 year and 7 months later (in July 2015), thereby departing from the standard of 1 year that prevailed thereafter. Thus, we

[9] https://www.esrb.europa.eu/national_policy/ccb/html/index.en.html

Fig. 1.1. Announced CCyB levels over time for the 18 countries having activated (in %)



Source: European Systemic Risk Board, Bank of International Settlement

Note: CCyB levels have been represented from the moment when they were officially announced i.e., in practice 1 year before they become effective. As of 31 March 2022.

begin our dataset in 2014. Details on the identification of announcement dates are presented in A.

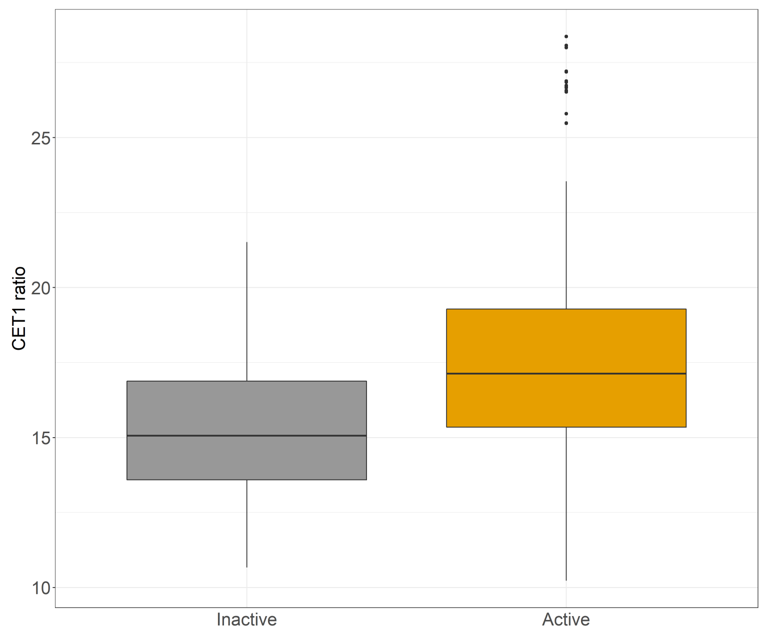
Third, we filter out all dates with confounding shocks. Designated authorities sometimes announce multiple decisions jointly with CCyB changes. For instance, the UK increase of July 5th, 2016 came together with a reduction in PRA buffers, while the Czech release of March 16th, 2020 happened on the same day as a reduction in monetary policy interest rates. We screen press releases individually to identify potential joint announcements, and filter out all dates on which other changes were announced.

Fourth, we calculate bank-specific shocks. For that purpose, we limit ourselves to publicly-available information that investors could be using. We rely on country-level bank exposures coming from the EBA annual transparency exercise that provides credit risk exposures of the largest banks to their 10 largest borrowing countries. Those exercises provide "detailed bank-by-bank data on capital positions, risk exposure amounts, leverage exposures and asset quality" for the largest banks of the European Economic Area (EEA) at the highest level of consolidation.[10]

The EBA dataset informs on geographical exposures by type of exposure (e.g., corpo-

[10] `https://eba.europa.eu/risk-analysis-and-data/eu-wide-transparency-exercise`

Fig. 1.2. Average CET1 ratio of the domestic banking sector by frequency of CCyB hike at country level



Source: European Central Bank, authors' calculation
Note: This Figure displays the average CET1 ratio of domestic sectors by frequency of CCyB hikes by the macroprudential authority. *Inactive* countries never increased the CCyB, *Low* frequency countries increased it once to twice (BE, DE, EE, HR, IE, LT, LU, RO), and *High* frequency countries increased it at least three times.

rate - SME) and thus allows disentangling relevant credit risk exposures from non-relevant credit risk exposures. In doing so, we use the share of relevant *credit risk* exposures as an approximation for the share of relevant exposures. We disregard the country-allocation of trading book and securitization exposures. Credit risk exposures represent a large share of total risk-weighted exposures, and more detailed public information on country-level exposures are in any case not available. We also neglect any difference between risk-weighted exposure ratios and corresponding capital requirements. Using confidential supervisory data on French banks, we confirm that this approximation is very close to the true weights of national CCyB at the bank level. Therefore, informed market participants are able to measure quite precisely the real impact of the shock using the EBA data set.

We take into account the lag in the release of public information by the EBA. Precisely, the EBA publishes in December of year n data for the second semester of year $n-1$ and the first semester of year n. We assume that investors estimate CCyB shocks in year $n+1$ using data published by the EBA in December of year n on bank exposures at the end of the first semester of year n. Since the results of the first transparency exercise were published

in December 2015, we use exposures of the second semester of 2014 published in December 2015 to approximate perceived CCyB shocks prior to 2016. Although investors did not have precise information on bank country-level exposures then, we assume they were able to assess them using other public sources. This allows us to include more CCyB changes in our dataset. Our results remain robust to excluding those early announcements.

In some cases, multiple countries announce CCyB changes on the same day, or announcement windows overlap. In this case, we simply sum shocks at the bank-day level, in line with the consequence of those multiple announcements for the bank-specific CCyB. Banks CCyB shocks are thus computed on day t as:

$$\Delta CCyB_{b,t} = \sum_{c=1}^{N} \left\{ \Delta CCyB_{c,t} * \frac{RWA_{b,c,t}^{relevant,\,credit\,risk}}{\sum_{k=1}^{N} RWA_{b,k,t}^{relevant,\,credit\,risk}} \right\}. \tag{1.6}$$

We match these shocks with bank-level market data on stock prices (from Bloomberg) and 5-year CDS spreads (from Eikon, Bloomberg and Datastream). [11] For the estimation of Equations (1.4) and (1.5), we also match with information on banks CET1 ratio and, for banks belonging to the European Single Supervisory Mechanism, with OCR from confidential supervisory data (see descriptive statistics in Table 1.5).

We end up with a daily panel of stock returns for 52 European bank, and CDS spreads for 47 banks (see Table 1.7).[12] 44 CCyB increases and 8 releases affected at least one bank with observed CDS spreads or stock prices (see Table 1.8). Almost all releases occurred between March and July 2020 in the context of the Covid crisis. Two exceptions are the UK release on July 5th, 2016 following the Brexit vote, and the Hong-Kong release of October 14th, 2019 in a context of social protests. Increases were generally of 0.5 percentage points (26 occurrences), and otherwise could be of 0.25, 0.625 (in Hong-Kong), 0.75 or 1 percentage points (pp). Releases were generally of larger magnitude, up to -2.5 pp in Sweden.

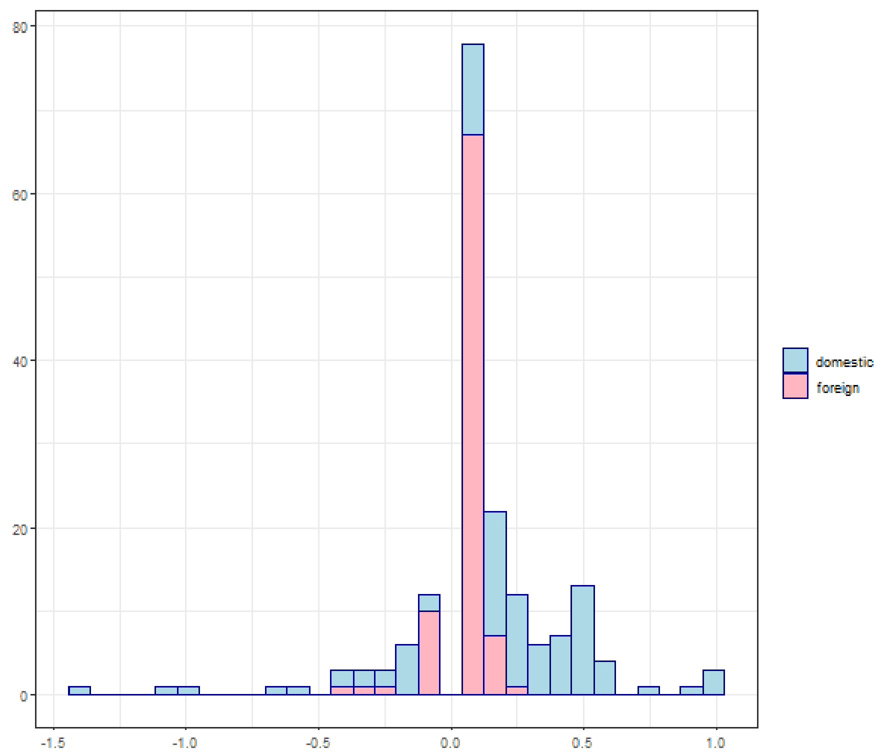
CCyB changes resulted in 500 bank-specific increases, and 131 bank-specific decreases. The distribution of those shocks is represented in Figure 1.3. While most shocks were modest (in particular due to small foreign exposures), 82 shocks amounted to more than 10 basis points, and 50 to more than 20 basis points. Since most banks in our sample are large

[11] We exclude banks' CDS or stock price series with insufficient liquidity based on the number of zero variations we observe.Precisely, we set to missing all observations when series are constant for at least 10 working days. If this procedure leads to setting to missing over 10% of the sample, we exclude the bank from the analysis.

[12] Our sample contains the largest and most internationally active banks which have rated CDS spreads and/or stock prices. There are two reasons why results may differ for smaller banks. First, if capital requirements have a non-linear effect on market prices, then smaller banks may react more strongly since they experience on average larger bank-specific shocks. Second, smaller and non-publicly traded banks may have less room for adjustment if they have a poorer access to equity markets, or are more reliant on their loan portfolios.

international banks, their share of foreign exposure can be large as evidenced in Figure 1.6. However, there is a domestic bias in banks exposures and the largest bank-specific shocks are experienced by banks resident of the activating country. The Table 1.6 reports the correlation matrix of the regressors on the days of CCyB hikes. In particular, bank-specific CCyB shocks do not largely correlate with the bucket of capitalisation or distance to OCR the bank belongs to.

Fig. 1.3. Distribution of bank-specific CCyB shocks (in %)



Note: Shocks of absolute magnitude above 5 bps. *Domestic* shocks are shocks affecting resident banks while *foreign* shocks affect non-resident banks.

5. Results

5.1. CCyB impact on country-level market variables

To begin with, we assess the impact of CCyB increases in a jurisdiction on country-level market variables. If CCyB increases convey private information on the state of a country's economy, we would expect those country-level variables to react on announcement

days. The estimates of Equation (1.2) and Equation (1.3) for country-level variables are gathered in Table 1.1, and show that country-level variables do not react to CCyB increases. This allows us to rule out the possibility that CCyB increases systematically convey private information on the state of a country's financial cycle. However, we observe an increase in sovereign CDS spreads upon CCyB releases (the coefficient on stock indices is also negative but insignificant). Therefore, markets could be interpreting releases as negative news from regulators.

Table 1.1: Impact of CCyB shocks on country-level market variables

Dependent Variables:	Δ CDS sov		Δ Stock Index	
	Baseline	Release	Baseline	Release
Model:	(1)	(2)	(3)	(4)
Δ CCyB	-0.0027		0.0005	
	(0.0043)		(0.0009)	
Δ CCyB × negative		-0.0123***		-0.0020
		(0.0045)		(0.0014)
Δ CCyB × positive		-0.0027		0.0005
		(0.0043)		(0.0009)
Observations	44,729	44,772	62,394	62,437
R^2	0.11396	0.11573	0.42282	0.42646
Adjusted R^2	0.11196	0.11371	0.42254	0.42618
No. dates	50	60	50	60

Notes: All country-level CCyB increases (including those having no bank of our sample exposed) are included in the sample, excluding Hong-Kong. All estimations are on a (0,2) event window with country fixed effects and controls. Driscoll-Kraay standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.

5.2. CCyB impact on bank CDS spreads

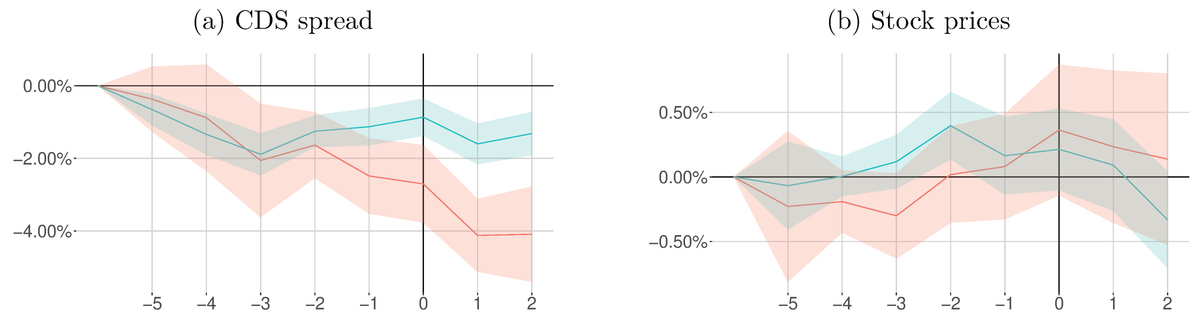
We now turn to the main part of the paper and investigate the impact of CCyB hikes on banks CDS spreads.

To get a graphical idea of this effect, we plot abnormal changes in CDS spreads around announcements of CCyB hikes. First, we estimate a model of normal change in CDS spreads: we estimate Equation (1.2), removing the shock variable and excluding all dates in the (-5,2) window. Using estimated coefficients, we compute abnormal changes in CDS spreads in those announcement windows.[13] Figure 1.4 panel (a) depicts the median cumulative

[13] This amounts to running the first-step of a two-step event study (see MacKinlay (1997)).

abnormal change in bank CDS spreads around CCyB announcements, separating for each shock affected from unaffected banks. Both have very similar pre-announcement trends, but while CDS spreads of unaffected banks do not react, those of affected banks fall markedly after announcements.

Fig. 1.4. Mean cumulated abnormal changes in CDS spreads and stock prices around CCyB hikes



Note: The red (green) line plots the mean cumulated abnormal change in CDS spread (panel (a)) and stock prices (panel (b)) for (un)affected banks, in basis points. (Un)affected banks are banks receiving a strictly positive (null) CCyB shock on announcement days. CCyB announcements with overlapping event windows are excluded. $x = 0$ designates the end of the day of the shock and ticks correspond to days. Bands correspond to 95% confidence bands.

We confirm this result by estimating Equation (1.2) for banks. Results are shown in Table 1.2 and indicate that CCyB increases lead to lower CDS spreads for affected banks. A 1 pp increase in bank-level capital requirements leads to 3.6% drop in CDS spreads.[14] This indicates that market participants consider that higher CCyB rates will lower debt holders' expected losses.[15] As such, the CCyB is expected to fulfill its main objective of increasing banks solvency.

We extend our main result in Column (2) by including CCyB releases along with hikes. We separate hikes from releases in the regression, to assess possible asymmetry in financial markets reaction. It turns out that CCyB announcements work both ways, with releases triggering an increase in CDS spreads. The estimated coefficients are three times larger for releases, but the very specific context of the COVID-19 pandemic during which most of the releases occurred makes a direct comparison of the coefficients difficult.[16] Also, since

[14] As we estimate a daily effect on a three-day window (0, 2), one have to compound the point estimate for three days to get the total effect of a 1 pp increase in requirements.

[15] CDS spreads price the probability of default (PD) and the loss given default (LGD) of the underlying, jointly with the risk aversion of parties. Under the assumption of risk neutrality, we have: $CDSspread = PD * LGD$.

[16] In particular, when the ECB announced a series of prudential loosening on 12 March 2020, it

country-level variables also reacted, part of the effect should be attributed to a signalling channel. Therefore, both coefficients are not directly comparable.

Table 1.2: Impact of CCyB shocks on bank CDS spreads

Dependent Variable:	Δ CDS	
	Baseline	Release
Model:	(1)	(2)
Δ CCyB	-0.0122**	
	(0.0060)	
Δ CCyB $\times$ negative		-0.0387***
		(0.0076)
Δ CCyB $\times$ positive		-0.0123**
		(0.0060)
Observations	89,383	89,519
R^2	0.12066	0.12125
Within R^2	0.12039	0.12097
No. dates	42	46
No. bank shocks	323	365

Notes: All estimations are on a (0,2) event window with bank fixed effects and controls. Driscoll-Kraay standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Our results are robust to a vast range of alternative specifications gathered in C. In Table 1.9, we test complementary shock specifications, while in Table 1.10 we verify that our results are robust to alternative specifications of normal CDS spread variations. As shown in Table 1.11, our results are significant on the (0,1) and the (0,2) window. In Table 1.12, we run the regression on an event window before the actual announcements (-3, -1) to assess possible anticipation of the announcements. While CCyB hikes were not anticipated in the few days before announcement, investors partially anticipated releases, which occurred in crisis context making them likely. Announcements of no CCyB change may also contain news if markets anticipated rate changes. Results presented in Table 1.12 also shows that such announcements have actually no impact on bank CDS spreads. This reinforces our claim that CCyB hikes come as a surprise. Finally, the impact of CCyB hikes also remains significant when removing country-level CCyB hikes one by one (Table 1.13), while Placebo

stated that these measures would be "be enhanced by the appropriate relaxation of the countercyclical capital buffer (CCyB) by the national macroprudential authorities", thereby pre-announcing subsequent releases. See `https://www.bankingsupervision.europa.eu/press/pr/date/2020/html/ssm.pr200312~43351ac3ac.en.html`.

tests confirm the validity of our event-study approach (Table 1.14).

Since country-level variables do not react to CCyB hikes, we interpret our results as evidence that markets anticipate banks to adjust their balance sheets in response to higher requirements. In this case, banks less capitalised and closer to their capital constraint are more likely to have to adjust their balance sheet structure, and should thus react more. Moreover, the relative impact of an additional unit of capital on banks' solvency should be higher for less capitalised banks.

We verify this by estimating Equation (1.4) and present results in Table 1.3. First, we separate banks depending on their CET1 ratio. Second, using confidential data on banks capital requirements, we are also able to compute the excess CET1 above the Overall Capital Requirements for banks of the the Single Supervisory Mechanism. Results confirm those hypotheses. CCyB hikes reduce CDS spreads of both highly and poorly capitalized banks, but the effect is five to ten times larger for less capitalized banks.

Table 1.3: Impact of CCyB increases on bank CDS spreads - bank characteristics

Dependent Variable:	Δ CDS	
Model:	(1)	(2)
Δ CCyB $\times$ Low CET1 ratio	-0.0853**	
	(0.0426)	
Δ CCyB $\times$ High CET1 ratio	-0.0146**	
	(0.0071)	
Δ CCyB $\times$ Low dist. OCR		-0.1000***
		(0.0293)
Δ CCyB $\times$ High dist. OCR		-0.0096*
		(0.0054)
Observations	70,531	64,576
R^2	0.12802	0.12159
Within R^2	0.12781	0.12130
No. dates	39	31
No. bank shocks	279	215

Notes: Interaction variables are dummies depending on the banks position relative to the median. All estimations are on a (0,2) event window with bank fixed effects and controls. Driscoll-Kraay standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Overall, our results show that CCyB hikes trigger a fall in banks CDS spreads, in particular for banks closer to their regulatory capital requirement.

5.3. CCyB impact on stock prices

In this section, we estimate Equation (1.3) and assess whether CDS spread drops are associated with changes in stock returns. As the sample of banks with listed stocks is larger than with CDS, we run the regressions on two samples: one including all stocks in the sample, and one covering only banks present in the CDS regressions of Section 5.2.[17] Results are summarized in Table 1.4. CCyB increases are not associated with any systematic stock price movement. This can also be seen graphically in Figure 1.4 panel (b). These results are robust independently of bank characteristics, as highlighted in Table 1.15, which presents the results of Equation (1.5).

We propose three broad categories of rationales that may explain why CCyB hikes leave stock returns unaffected.

First, if banks were to adjust their balance sheet through an increase in capital, pecking-order (Myers and Majluf (1984)) and market timing (Baker and Wurgler (2002)) theories predict this should have no impact on stock prices. Capital structure matters only in the presence of information frictions. Thus, equity issuance due to higher capital requirements do not affect stock prices since they do not convey any private information. As in Cornett and Tehranian (1994), we indeed find that regulatory-driven capital structure adjustments do not affect stock prices since they do not convey any bank manager private information. Besides, as CCyB hikes are relatively modest and announced one year before they become applicable, banks may be able to adjust with retained earnings only and avoid non-informational transaction costs attached to equity issuance.

Second, there may be multiple optimal balance sheet choices for shareholders. In a mean-variance framework à la Markowitz (1952), there is an infinite number of optimal portfolios along the capital market line. In our setting, markets could perceive the CCyB to cause a reduction in bank profits, with risk-adjusted profits remaining constant. Our results are also consistent with the existence of an optimal *range* of balance sheet structures. In trade-off theories, any increased capital requirement would automatically force a firm to deviate from its optimal leverage, and entail lower stock prices (Kraus and Litzenberger (1973)). However, if shareholders target an optimal range of leverage instead of a specific ratio, any CCyB increase allowing banks to remain in that range may come at no cost for shareholders. In other words, the effect of requirements on stock prices may be non-linear depending on whether it forces managers to depart from their optimal balance sheet structure range.

Finally, coordination challenges among competing banks may lead them to choose capital structures inferior to those that could be set by a regulator, for instance if banks are unwilling

[17] There are 32 banks with defined stock returns and undefined CDS spreads, and 8 banks with the opposite.

to individually adjust capital structures out of fear of losing market shares. In that case, shareholders would potentially not object to a regulator setting higher capital requirements across the board.

Disentangling those different effects is beyond the scope of this paper. What we show is that observed CCyB increases did not trigger any stock price decline. This absence of reaction implies that regulators were able to enhance banks' solvency at no significant cost for shareholders.

Table 1.4: Impact of CCyB increases on bank stock returns

Dependent Variable:	Δ Stock			
Sample:	All		CDS sample	
Shock:	Baseline	Release	Baseline	Release
Model:	(1)	(2)	(3)	(4)
Δ CCyB	0.0014		0.0001	
	(0.0025)		(0.0044)	
Δ CCyB × negative		0.0034		0.0013
		(0.0048)		(0.0056)
Δ CCyB × positive		0.0015		0.0002
		(0.0025)		(0.0044)
Observations	119,561	119,725	68,652	68,752
R^2	0.39827	0.39707	0.41761	0.41642
Within R^2	0.39785	0.39666	0.41722	0.41603
No. dates	43	49	42	48
No. bank shocks	363	418	241	275

Notes: CDS sample regressions estimate the stock return equation on points of the panel when CDS spreads are defined. All estimations are on a (0,2) event window with bank fixed effects and controls. Driscoll-Kraay standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.

6. Conclusion

In this paper, we exploit the institutional setup of the CCyB in the EEA to directly estimate the effect of capital requirements on financial markets. Our identification rests upon two features: CCyB hikes are quarterly announcements by national authorities, and they heterogeneously affect all banks of the EEA. We use this setup to assess how markets factor capital requirement increases in CDS spreads and stock prices.

We show that hikes in CCyB rates are perceived as increasing bank solvency, at no

significant cost for shareholders. We claim that these effects relate to the capital constraint itself, as opposed to the potential signal conveyed on the state of the financial cycle. The impact on CDS spreads is materially larger for banks poorly capitalised, as they are more likely to adjust to higher requirements and their solvency should benefit more from an additional unit of capital. These results are important to assess the costs and benefits of capital requirements. Our results suggest that regulators were able to enhance banks' solvency at no significant cost for shareholder. Looking ahead, regulators may be able to further increase CCyB rates without significantly affecting shareholder value.

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A. Identification of CCyB announcement dates

To identify announcement days, we watch out for two pitfalls. First, there may be distinct *macroprudential* and *designated* authorities, with the former making CCyB recommendations and the latter taking CCyB decisions. Second, authorities may be providing guidance on the path of future CCyB rates.

European law mandates the establishment of both a *macroprudential authority* in charge of conducting macroprudential policy,[18] and a *designated authority* in charge of deciding CCyB rates.[19] Both autorities can be distinct.[20] Among countries that activated, Bulgaria, Croatia, Denmark, Germany, Iceland, and Luxembourg have a distinct macroprudential authority publishing recommendations 1 to 3 month prior to the designated authority decision. In all cases, those recommendations have been followed up by a decision. We consider the relevant announcement day to be the first public announcement of the CCyB change, may it be a *macroprudential authority* recommendation or a *designated authority* decision.

When authorities provide guidance on the path of future CCyB rates, we exclude the initial guidance as well as the subsequent official announcement. Forward guidance announcements would not be directly comparable to official announcements, since they become effective more than a year after they are made. Subsequent announcements should be largely anticipated. In Denmark, the macroprudential authority (the Systemic Risk Council) can provide forward guidance on future recommendations in the same press release as that of the current recommendation (it occurred on 9 April 2018, 25 September 2018, 26 March 2018, and 1 October 2019). French and British designated authorities also used forward guidance (resp. on 14 December 2021, and on 27 June 2017 and 13 December 2021). Several CCyB releases were also announced in the press before being formally announced, and are excluded (France on 13 March 2020, and Ireland on 13 March 2020).

B. The CCyB framework in the EEA

Capital requirements are usually defined by national regulatory authorities as an equal top-up for all their domestic banks. On the contrary, to ensure that banks are sufficiently capitalized relative to their geographic exposures, each national authority must determine a

[18]See Recommendation ESRB/2011/3 of the European Systemic Risk Board on the macro-prudential mandate of national authorities: `https://www.esrb.europa.eu/pub/pdf/recommendations/ESRB_2011_3.en.pdf`

[19]See Article 136(1) of CRD IV.

[20]A full list of countries depending on their institutional arrangement is available here: `https://www.esrb.europa.eu/national_policy/shared/pdf/esrb.191125_list_national%20_macroprudential_authorities_and_national_designated_authorities_in_EEA_Member_States.en.pdf`

CCyB rate for exposures to all countries in the world. The delay before the entry into force must not exceed one year after the publication of the decision, and can be shorter only under exceptional circumstances. Then, each bank domiciled in country d must compute a specific CCyB rate, defined as the average of country-level CCyB rates fixed by the authority of country d, weighted by the bank's capital requirement due to relevant risk-weighted exposure to each country. Relevant exposures include all exposures to the non-financial private sector. The bank-specific CCyB rate can thus be expressed as follows:

$$CCyB_{b,d,t} = \sum_{c=1}^{N} \left\{ C\tilde{CyB}_{d,c,t} * \frac{Requirement_{b,c,t}^{RWA\,relevant}}{\sum_{k=1}^{N} Requirement_{b,k,t}^{RWA\,relevant}} \right\}, \tag{1.7}$$

with b the bank, t the date, d the domestic country and c in $1, ..., N$ the countries. $C\tilde{CyB}_{d,c,t}$ is the CCyB rate applying to banks domiciled in country d for their exposures in country c.

To avoid distortion to the level playing field, the Basel III rules include a reciprocity framework, according to which national authorities should apply to their domestic banks the rate decided in each of the participating countries for its banks' domestic exposures, so that $C\tilde{CyB}_{d,c,t} = C\tilde{CyB}_{c,t}$. National authorities have one year after the publication of a new CCyB rate by a foreign authority to apply it on the banks they supervise. This reciprocity applies up to a CCyB rate of 2.5%. Above, the reciprocity is purely voluntary. If some countries do not implement any CCyB (for instance if it is not part of the Basel III agreements), national authorities of participating countries are free to set any CCyB rate $CCyB_{d,c,t}$ on this country for their banks. This has never occurred so far, meaning that implicitly $C\tilde{CyB}_{d,c,t} = 0$ for all countries d in the Basel Group and all countries c outside it.

The CCyB was included in the European regulatory financial framework via the EEA relevant *Capital Requirements Directive IV* (CRD IV),[21] adopted in 2013 and then transposed into national laws. CRD IV formalizes the capital regulations introduced in Basel III agreements, among which the CCyB.

This directive strengthens the reciprocity framework, making it automatic without need for domestic authorities to formally reciprocate foreign rates: up to 2.5%, banks must automatically apply the CCyB rate set by national authorities (inside and outside the EEA) on their own country.[22] Above 2.5%, the reciprocity remains voluntary. Moreover, designated

[21] Articles 130, 135, 136, 140 of Directive 2013/36/EU of the European Parliament and of the Council of 26 June 2013: `https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:32013L0036&from=FR`

[22] The rule for implementation delays for EEA banks differs between EEA and non-EEA rates. For the former, the implementation delay is the one decided by the designated authority setting the rate. For countries outside the EEA, the implementation date of the reciprocity is one year after the announcement of the new rate by the foreign state, whatever its domestic implementation delay. Nevertheless, all countries

authorities in the EEA can decide to apply higher CCyB rates on exposures to a given non-EEA country if it deems its current CCyB insufficient. In practice, no CCyB rate has so far exceeded 2.5% and no designated authority in the EEA has decided to top-up non-EEA CCyB rates. Consequently, the CCyB rate that applies to an EEA bank b exposed to N countries c, and up to 2.5%, is:

$$CCyB_{b,t} = \sum_{c=1}^{N} \left\{ CCyB_{c,t} * \frac{Requirement_{b,c,t}^{RWA\,relevant}}{\sum_{k=1}^{N} Requirement_{b,k,t}^{RWA\,relevant}} \right\} \tag{1.1}$$

In the European stacking order of capital requirements, the CCyB enters the so-called *Combined Buffer Requirement* (hereafter CBR), along with the Capital Conservation Buffer, the Systemic Risk Buffer, the Global Systemically Important Institution buffer and the Other Systemically Important Institution buffer.[23] In the stacking order, the CBR is above the Pillar 1 and the Pillar 2 Requirement but below the Pillar 2 Guidance (Figure 1.5). The breach of the CBR by a bank has two consequences. First, the bank is restricted in the amount of capital it can distribute in dividend and share buyback, by the so-called *Maximum Distributable Amount* (hereafter MDA).[24] Second, the bank has to present a *Capital Conservation Plan*, including profit forecasts and intended measures to bridge the gap in capital. If the supervisor rejects the plan, it can require the institution to increase capital in a specified period and consequently lower the MDA.[25] Dividend restrictions and the negative ensuing signal ensure banks have incentives to comply with the CCyB and even keep a buffer above the CBR.

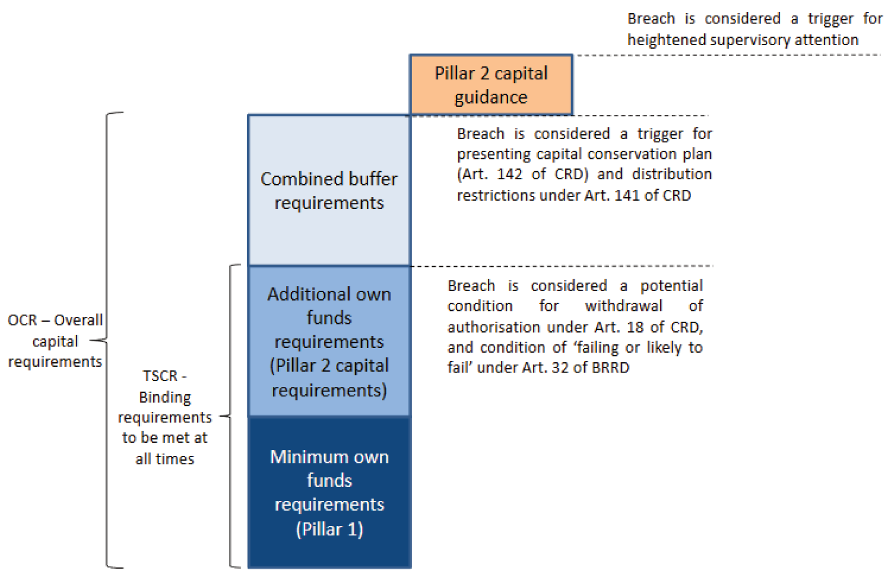
have so far used a one-year implementation delay, making the difference irrelevant.

[23]See `https://eba.europa.eu/single-rule-book-qa/-/qna/view/publicId/2015_1759`

[24]Article 141 of CRD IV

[25]Article 142 of CRD IV

Fig. 1.5. Stacking order of capital requirements, and sanctions for breaching



Source: European Banking Authority, Pillar 2 Roadmap, p.4

C. Additional tables

Table 1.5: Bank descriptive statistics

Statistic	Unit	N	Mean	St. Dev.	Min	Max
CDS spread growth	%	95,733	−0.01	2.4	−4.9	5.3
Stock return	%	105,680	0.01	1.8	−3.5	3.6
Total assets	Bn€	48,479	397.9	521.6	1.7	2,519.5
CET1 ratio	%	111,709	15.1	3.4	1.5	37.1
Dist. OCR	*pp*	85,912	4.6	3.3	−11.5	25.1

Table 1.6: Correlation matrix of regressors

	$\Delta CCyB$	High CET1	High dist. OCR	Stoxx600 fi.	Yield curve	Ten year AAA	Vstoxx
$\Delta CCyB$	1	0.199	0.114	-0.127	-0.013	0.061	-0.024
High CET1	0.199	1	0.429	-0.084	-0.030	0.196	-0.009
High dist. OCR	0.114	0.429	1	-0.122	-0.027	0.114	-0.024
Stoxx600 fi.	-0.127	-0.084	-0.122	1	0.274	-0.207	0.377
Yield curve	-0.013	-0.030	-0.027	0.274	1	-0.020	0.263
Ten year AAA	0.061	0.196	0.114	-0.207	-0.020	1	-0.252
Vstoxx	-0.024	-0.009	-0.024	0.377	0.263	-0.252	1

Notes: This table presents the correlation matrix of the regressors to Equation (1.4) on days of shock.

Table 1.7: Number of banks by country of residence depending on market data availability

Country	Nb bank CDS	Nb banks Stocks	Nb banks either	Nb banks both
Austria	3	3	3	3
Belgium	2	1	2	1
Bulgaria	0	1	1	0
Cyprus	0	2	2	0
Denmark	1	3	3	1
Estonia	0	1	1	0
Finland	1	1	1	1
France	6	3	6	3
Germany	7	4	9	2
Greece	3	4	4	3
Hungary	0	1	1	0
Ireland	3	2	3	2
Italy	5	7	7	5
Malta	0	1	1	0
Netherlands	4	2	4	2
Norway	0	2	2	0
Portugal	3	1	3	1
Romania	0	1	1	0
Slovenia	0	1	1	0
Spain	3	3	3	3
Sweden	2	3	3	2
United Kingdom	4	5	5	4
Total	47	52	66	33

Notes: Number of banks by country included in at least one EBA transparency exercise, depending on whether we find information on that bank's CDS spreads and stock prices.

Table 1.8: Descriptive statistics of CCyB shocks

Date	Country	Δ CCYB (pp)	Banks	CDS	Stock	Median (bp)	Mean (bp)	Max (bp)
2014-09-10	SE	1.00	10	5	9	8.86	18.87	59.92
2015-01-27	HK	0.62	3	2	1	0.32	2.58	7.18
2015-06-23	SE	0.50	10	5	9	4.43	9.43	29.96
2015-12-18	CZ	0.50	4	4	4	3.55	4.11	8.26
2016-01-14	HK	0.62	3	2	2	0.34	2.36	6.55
2016-03-15	SE	0.50	10	5	9	4.67	9.49	29.85
2016-03-29	GB	0.50	43	33	33	1.12	4.40	40.86
2016-07-26	SK	0.50	3	2	3	2.42	2.28	3.03
2016-12-15	NO	0.50	6	4	6	5.78	9.88	32.10
2017-01-27	HK	0.62	3	2	2	0.35	2.63	7.36
2017-06-13	CZ	0.50	4	4	4	5.08	5.22	9.40
2017-06-27	GB	0.50	49	39	37	1.50	4.25	40.09
2017-07-10	SK	0.75	4	3	4	4.44	3.98	4.96
2017-12-20	DK	0.50	7	3	7	12.83	19.53	50.00
2017-12-21	LT	0.50	3	1	3	3.10	2.46	3.13
2018-01-10	HK	0.62	3	2	3	7.37	5.83	9.91
2018-06-11	FR	0.25	36	30	25	0.46	2.80	19.51
2018-06-22	LT	0.50	4	1	4	2.68	2.44	3.38
2018-07-03	SK	0.25	5	4	5	1.39	1.43	2.34
2018-07-05	IE	1.00	8	8	7	8.83	31.09	97.89
2018-07-30	SE	0.50	13	8	10	2.46	7.42	28.72
2018-09-26	BG	0.50	5	3	5	3.43	12.27	46.81
2018-12-10	LU	0.25	20	17	13	0.35	0.51	3.11
2018-12-13	NO	0.50	8	5	8	6.25	13.55	50.00
2019-03-18	FR	0.25	36	29	25	0.50	2.74	19.95
2019-03-29	BG	0.50	6	4	5	2.92	10.57	48.13
2019-05-23	CZ	0.25	5	5	5	2.36	2.50	4.91
2019-06-28	BE	0.50	9	8	5	1.71	8.69	41.60
2019-06-28	DE	0.25	37	27	28	0.68	3.38	18.32
2019-07-23	SK	0.50	5	4	5	2.80	2.70	3.86
2019-10-14	HK	-0.50	3	2	3	-6.78	-5.45	-9.23
2019-11-29	LU	0.25	21	18	15	0.41	0.54	2.88
2019-12-20	BG	0.50	6	4	5	2.92	10.57	48.13
2020-03-11	BE	-0.50	11	10	6	-1.21	-7.33	-42.26
2020-03-13	SE	-2.50	11	7	9	-20.80	-41.65	-139.37
2020-03-18	DE	-0.25	45	33	34	-0.44	-2.82	-20.36
2020-03-18	FR	-0.50	45	35	33	-0.73	-4.50	-40.99
2020-03-18	IE	-1.00	8	8	6	-5.12	-18.24	-67.33
2020-03-18	LT	-1.00	3	1	3	-6.44	-5.24	-7.55
2020-07-07	SK	-0.50	5	3	5	-2.73	-2.64	-3.96
2021-03-10	CZ	0.50	5	5	5	5.02	4.79	9.10
2021-05-27	CZ	0.50	5	5	5	5.02	4.79	9.10
2021-06-17	NO	0.50	10	5	8	4.81	11.29	50.00
2021-06-28	CZ	0.50	5	5	5	5.02	4.79	9.10
2021-09-16	BG	0.50	5	3	5	4.65	13.10	48.28
2021-09-29	SE	1.00	10	7	8	11.90	18.71	55.72
2021-10-15	RO	0.50	9	2	9	2.07	7.56	50.00
2021-11-29	EE	1.00	3	1	3	10.01	37.76	97.72
2021-12-16	BG	0.50	5	3	5	4.65	13.10	48.28
2021-12-24	DK	1.00	7	3	7	23.52	39.70	100.00
2022-01-31	DE	0.75	42	31	28	2.07	11.28	61.22
2022-02-16	HR	0.50	5	4	5	1.64	2.26	4.71
	Total positive	44.00	500	365	399	1.62	7.27	100.00
	Total negative	8.00	131	99	99	-1.13	-8.09	-139.37

Table 1.9: Impact of CCyB increases on bank CDS spreads - alternative shocks

Dependent Variable:			Δ CDS		
	Domestic	Foreign	Large	Activation	Dummy
Model:	(1)	(2)	(3)	(4)	(5)
Δ CCyB	-0.0084*	-0.0661**	-0.0076*	-0.0123*	
	(0.0043)	(0.0268)	(0.0040)	(0.0063)	
dummy					-0.0048**
					(0.0020)
Observations	89,383	89,383	89,181	89,268	89,383
R^2	0.12064	0.12070	0.12054	0.12062	0.12093
Within R^2	0.12038	0.12043	0.12028	0.12036	0.12066
No. dates	13	42	21	17	42
No. bank shocks	48	280	65	179	323

Notes: Equation (1) studies the effect of country-level announcements on domestic banks only, and Equation (2) on foreign banks. Equation (3) looks at the effect of shocks in the fourth quartile of magnitude. Equation (4) investigates the effect of first-time CCyB activations in each country. Equation (5) examines the effect of dummy shocks affecting identically all banks subject to a shock in the baseline specification.All estimations are on a (0,2) event window with bank fixed effects and controls. Driscoll-Kraay standard errors in parentheses.*p<0.1; **p<0.05; ***p<0.01.

Table 1.10: Impact of CCyB increases on bank CDS spreads - alternative control variables

Dependent Variable:	Δ CDS				
	StoxxBanks	ItraxxSeniorFin	ItraxxEur	CDS sov	No control
Model:	(1)	(2)	(3)	(4)	(5)
Δ CCyB	-0.0122**	-0.0078*	-0.0094**	-0.0125**	-0.0144***
	(0.0060)	(0.0041)	(0.0046)	(0.0063)	(0.0055)
Fixed-effects					
bank	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	89,383	89,383	89,383	82,878	107,488
R^2	0.12057	0.26840	0.23722	0.17425	0.00030
Within R^2	0.12031	0.26818	0.23699	0.17401	6.22×10^{-5}
No. dates	42	42	42	42	42
No. bank shocks	323	323	323	323	323

Notes: Alternative specifications of the 4-factor model by changing the stock return factor with the growth rates of the following benchmarks: Stoxx600 Bank in Column (1), Itraxx Senior Financial in Column (2), Itraxx Europe in Column (3), and the sovereign CDS spread of the banks country of residence in Column (4). Column (5) houses the result without any control variable. All estimations are on a (0,2) event window. Driscoll-Kraay standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 1.11: Impact of CCyB increases on bank CDS spreads - persistence

Dependent Variable:	Δ CDS					
	(0,0)	(0,1)	(0,2)	(0,3)	(0,4)	(0,5)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Δ CCyB	-0.0096	-0.0136*	-0.0122**	-0.0068	-0.0028	-0.0017
	(0.0126)	(0.0078)	(0.0060)	(0.0060)	(0.0050)	(0.0051)
Observations	89,973	89,673	89,383	89,106	88,829	88,578
R^2	0.11984	0.11897	0.12066	0.12065	0.12006	0.12080
Within R^2	0.11956	0.11869	0.12039	0.12036	0.11979	0.12055
No. dates	43	43	43	44	44	44
No. bank shocks	327	327	327	325	322	322

Notes: Event windows are defined with a tuple where the first element refers to the first day of the event, and the second to the last day. Days are counted relative to day 0 - the day of the announcement itself. All estimations are with bank fixed effects and controls. Driscoll-Kraay standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 1.12: Impact of CCyB increases on bank CDS spreads - no announcements and pre-trend

Dependent Variable:		Δ CDS	
	No change value	No change dummy	(-3,-1)
Model:	(1)	(2)	(3)
Δ CCyB	0.0019		-0.0011
	(0.0013)		(0.0099)
Dummy		0.0005	
		(0.0009)	
Observations	88,658	88,658	89,377
R^2	0.11998	0.11995	0.11863
Within R^2	0.11973	0.11970	0.11839
No. dates	302	302	60
No. bank shocks	3,108	3,108	580

Notes: No change value regresses CDS spread growth on a shock equal to bank-specific exposure shares on all dates when some authority announces a constant CCyB rate. *No change dummy* regresses CDS spread growth on a shock equal to 1 whenever a bank is exposed to an announcement of no CCyB change by some authority. Dates when any authority announces a CCyB change are excluded from the sample. (-3,-1) estimates the baseline regression on the (-3,-1) window to check for pre-trend. All estimations are on a (0,2) event window with bank fixed effects and controls, unless specified otherwise. Driscoll-Kraay standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 1.13: Robustness to removing one by one the dates of CCyB increases

	Estimate	P-value
2014-09-10	-0.015	0.055
2015-01-27	-0.013	0.040
2015-06-23	-0.013	0.045
2015-12-18	-0.012	0.043
2016-01-14	-0.013	0.040
2016-03-15	-0.014	0.038
2016-03-29	-0.011	0.060
2016-07-26	-0.013	0.041
2016-12-15	-0.013	0.038
2017-01-27	-0.013	0.040
2017-06-13	-0.012	0.048
2017-07-10	-0.013	0.041
2017-12-20	-0.013	0.037
2017-12-21	-0.013	0.041
2018-01-10	-0.013	0.041
2018-06-11	-0.010	0.059
2018-06-22	-0.013	0.041
2018-07-03	-0.012	0.046
2018-07-05	-0.020	0.051
2018-07-30	-0.012	0.051
2018-09-26	-0.013	0.040
2018-12-10	-0.013	0.041
2018-12-13	-0.012	0.046
2019-03-18	-0.014	0.026
2019-03-29	-0.013	0.041
2019-05-23	-0.013	0.041
2019-06-28	-0.010	0.077
2019-07-23	-0.012	0.042
2019-11-29	-0.012	0.042
2019-12-20	-0.013	0.040
2021-03-10	-0.013	0.041
2021-05-27	-0.013	0.041
2021-06-17	-0.013	0.041
2021-06-28	-0.013	0.041
2021-09-16	-0.013	0.041
2021-09-29	-0.013	0.041
2021-10-15	-0.013	0.041
2021-11-29	-0.013	0.041
2021-12-16	-0.013	0.041
2021-12-24	-0.013	0.041
2022-01-31	-0.013	0.041
2022-02-16	-0.013	0.041

Notes: Point estimates and p-values of the baseline regression estimated by removing one by one all days with CCyB increases.

Table 1.14: Impact of CCyB increases on bank CDS spreads - placebo

Dependent Variable:	Δ CDS
Model:	(1)
Δ CCyB	-0.0029
	(0.0052)
Observations	89,383
R^2	0.12063
Within R^2	0.12036

Notes: For each date of CCyB change, shocks are randomly drawn without replacement in the cross-section of banks. Shocks are then rolled onto a (0,2) event window. All estimations are on a (0,2) event window with bank fixed effects and controls. Driscoll-Kraay standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.

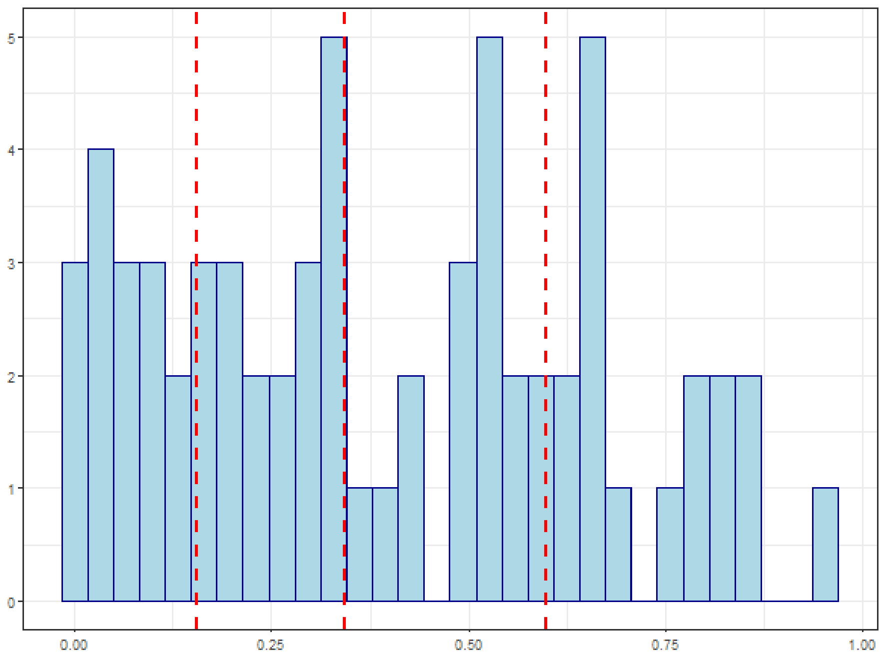
Table 1.15: Impact of CCyB increases on bank stock returns - bank characteristics

Dependent Variable:	Δ Stock	
Model:	(1)	(2)
Δ CCyB $\times$ Low CET1 ratio	-0.0283	
	(0.0219)	
Δ CCyB $\times$ High CET1 ratio	0.0027	
	(0.0039)	
Δ CCyB $\times$ Low dist. OCR		-0.0312
		(0.0202)
Δ CCyB $\times$ High dist. OCR		-0.0029
		(0.0025)
Observations	54,578	43,890
R^2	0.41891	0.43197
Within R^2	0.41846	0.43144
No. dates	38	28
No. bank shocks	208	144

Notes: Interaction variables are dummies depending on the banks position relative to the median. All estimations are on a (0,2) event window with bank fixed effects and controls. Driscoll-Kraay standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01.

D. Additional charts

Fig. 1.6. Distribution of the share of relevant foreign exposures in total relevant exposures across banks as of the largest observation (Q2 2021)



Note: Distribution across all banks which experience at least one CCyB shock and for which we observe CDS spreads or stock prices. The dashed lines represent from left to right the first quartile, the median, and the third quartile of the distribution.

Chapter 2

CDS Trading Strategies and Credit Risk Reallocation

This chapter is based on a paper co-authored with Thibaut Piquard (Banque de France).

Abstract

We study how Credit Default Swaps (CDS) reallocate credit risk between investors. Using data on granular holdings of debt and CDS referencing non-financial corporations, we propose a methodology to disentangle CDS positions between three strategies: hedging, speculation, and arbitrage. In our dataset, arbitrage remains anecdotal and the bulk of net positions are speculative, which implies that CDS increase total exposures at default. Hedgers purchase CDS to shed off their most concentrated exposures, while speculators sell them as a complement to debt to gain synthetic leverage. CDS also facilitate risk-taking by speculators and allow hedgers to cover their riskiest exposures.

1. Introduction

Credit Default Swaps (CDS) are controversial financial instruments - "weapons of mass destruction" according to W. Buffet. On the one hand, CDS might improve the allocation of credit risk allowing illiquid but optimistic investors to gain credit risk exposure (Oehmke and Zawadowski, 2015). On the other hand, CDS reduce monitoring incentives because of the empty creditor problem (Bolton and Oehmke, 2011), and may even facilitate agents' coordination to "bad" equilibria (Bruneau et al., 2014). These contributions primarily focus on how CDS affect asset prices or the risk of referenced entities. However, they remain silent on the distributional consequences of CDS on investor-level risk for at least two reasons.

First, CDS are a zero-sum game in aggregate and payoffs are merely transfers within the financial system. However, recent contributions as Gabaix (2011), Galaasen et al. (2020) or Baena et al. (2022) stress how individual shocks may affect aggregate outcomes and credit supply in particular. As such, individual credit risk exposures may matter for financial

stability.[1] Second, studying the distribution of credit risk requires granular data on multiple instruments (loans, bonds, and CDS), which are difficult to access and process and have only recently been a focus of researchers.

Using granular quarterly data on both debt and CDS exposures of French investors to non-financial corporations (NFC) and euro area (EA) banks and investment funds to French NFCs from $2016Q1$ to $2021Q4$, we provide new answers to how CDS reallocate credit risk across investors. This occurs in three manners.

First, CDS trading may increase the *total* outstanding amount of credit risk exposures, or exposures at default (EAD), to the extent that not all CDS purchases offset preexisting debt exposures. Second, CDS trading may alter the *concentration* of exposures across investors. Third, if CDS increase total exposures, CDS trading may also alter the *composition* of outstanding credit risk.

To guide our investigation, we first contribute to the literature by disentangling CDS positions along three trading motives, each with different consequences for credit risk reallocation: arbitrage, hedging, and speculation. To do so, we leverage on our granular dataset at the investor-reference entity-quarter level to identify whether debt and CDS exposures offset or amplify each other, whether the debt is a bond or a loan, and whether positions are acquired simultaneously or successively.

Arbitrageurs take offsetting positions in CDS and debt to benefit from relative price discrepancies. We identify them as offsetting positions where debt takes only the form of bonds, and where both the debt and the CDS positions are simultaneously acquired. This strategy is anecdotal and represents 2% of CDS purchasers, and a mere 0.03% of CDS sellers. These positions likely correspond to arbitrage, as they tend to relate to hedging ratios and residual maturity ratios close to one, and to negative CDS-bond bases.

Hedgers use CDS as an insurance product to downsize corresponding credit risk exposures, either in reaction to shocks, or to maintain lending relationships. We identify them as offsetting positions where either the CDS is purchased after the debt position, or both are jointly acquired and the debt is at least partially a loan. Hedging represents 19% of CDS purchases, and almost exclusively corresponds to hedging in response to shocks. Other types of offsetting CDS purchases add to 6% of net positions.

Finally, speculators use CDS as an alternative venue to amplify debt exposures or to gain a credit risk exposure without holding the underlying debt. Speculation represents 73% of

[1] Studying credit risk at the individual level also finds support in bank capital regulation, which constrains the use of CDS for hedging purposes to debt instruments on the same reference entity. Article 213 of the EU Capital Requirements Regulation (CRR) stipulates that "credit protection deriving from a guarantee or credit derivative shall qualify as eligible unfunded credit protection where all the following conditions are met: (a) the credit protection is direct [...]".

CDS purchases, while virtually all CDS sellers are speculators. For speculators purchasing CDS, the objective is to gain short credit risk exposures because short-selling debt may involve costly frictions to which buying CDS is not subject.[2] We find that 95% of short credit risk exposures trade through CDS.

As CDS selling seldom corresponds to hedging or arbitrage, almost every CDS sold will increase the selling investors' EAD. Whether the transaction also increases total outstanding EAD then depends on the share of short speculators among CDS purchasers. In our dataset, accounting for CDS leads to an increase in EAD against CDS-referenced entities of 10 to 15%.

In a model of risk-sharing with fixed costs, Atkeson et al. (2015) logically predict that hedgers offset their largest debt exposures. By contrast, theory yields conflicting predictions on whether CDS should be used as a substitute or a complement to debt by speculators. They could substitute debt with CDS following a risk-sharing motive. Additionally, CDS have lower trading costs than debt in Oehmke and Zawadowski (2015) where investors optimally choose their preferred instrument depending on their liquidity profile. However, according to Che and Sethi (2014), speculators take advantage of CDS lower margin requirements to leverage their beliefs and double up their existing debt exposures.

There are two challenges in identifying the effect of exposure concentration on CDS trading. First, becoming a CDS reference may affect the reference entity's behavior with consequences on exposure concentration and riskiness. Empirical contributions on the effect of CDS on reference entity debt tend to show that CDS trading induces firms to issue more debt at lower rates (Hirtle, 2009; Saretto and Tookes, 2013), and ultimately become riskier (Subrahmanyam et al., 2014). We restrict our analysis to reference entities on which CDS are traded at least once over the sample, so that they all have a priori similar incentives to increase leverage.

The second and main challenge with relating CDS trading to debt concentration is that both positions may be jointly determined. Investors may be taking larger debt exposures knowing they can partly shed them off in the CDS market, and smaller debt exposures if they can sell CDS on the same reference entity. To circumvent this issue, we instrument each investor-reference entity debt exposure by the share of the reference entity's gross debt in the universe if reference entities ever held by the investor. The instrument namely posits investors allocate their debt holdings proportionally across reference entities.

Addressing these two identification challenges is one of the key innovations of this paper, which thus improves on the standard theoretical (Atkeson et al., 2015) and empirical

[2]Short-selling debt requires locating securities lenders and managing the risk of not finding securities sellers upon termination (Duffie et al., 2002; Nashikkar et al., 2011).

(Oehmke and Zawadowski, 2017; Jiang et al., 2021) tradition that assumes debt exposures as given when looking at the effects of CDS.[3]

Consistent with predictions from Atkeson et al. (2015), banks and dealers use CDS to hedge their most concentrated exposures, while concentration does not seem to matter for fund hedgers. This could relate to stronger regulation on banks' exposure concentration.[4] The effects are economically important: for every additional percentage point of debt concentration, the probability of hedging that exposure increases by almost 31pp for banks, and by as much as 113pp for dealers (to be compared with median debt exposure concentrations of respectively 0.11pp and 0.07pp among potential hedgers).

Furthermore, our results corroborate Che and Sethi (2014) view for banks and investment funds on speculators. Conditional on holding some debt, investors sell more CDS if the reference entity debt accounts for a larger proportion of their debt portfolio. The absence of results on dealers is consistent with their role as intermediaries, their positions mirroring to a large extent the trading strategies of their counterparts. As for hedging, the effects are economically significant: the probability of selling CDS on top of existing debt exposures increases by 6pp for funds and as much as 103pp for banks for every additional percentage point of exposure concentration (to be compared with median debt exposure concentrations of respectively 0.5pp and 0.03pp among potential long speculators).

By definition, naked speculators trade CDS on exposures for which they have no underlying debt. However, we also find that banks and dealers tend to sell more CDS for country-rating exposures they already hold most of, again validating the considerations of Che and Sethi (2014).

In the last part of the paper, we ask whether CDS change the risk composition of exposures outstanding. There are at least four reasons why investors' incentives to trade CDS (relative to debt) may increase with reference entity risk. Disagreement on reference entity risk (Oehmke and Zawadowski, 2015), or incentives for hedging Atkeson et al. (2015) could both be higher for riskier firms. CDS may also require less initial margins than similar leveraged positions in the debt market, an advantage that grows with reference risk (Darst and Refayet, 2018). Finally, benefits from trade opacity could increase with reference entity riskiness (Jiang et al., 2021).

As for concentration, these analyzes may be subject to endogeneity as credit risk positions in debt and CDS are jointly determined. Investors trading CDS may reduce holdings of riskier debt securities knowing that CDS are relatively attractive for these risk levels. We

[3]This usually rests on the assumption that debt is less liquid than CDS.

[4]For instance, Article 394 of CRR requires banks to report all exposures exceeding 10% of their eligible capital, while Article 395 imposes a hard limit to exposure concentration of 25% of eligible capital.

address this concern by comparing the riskiness of debt portfolios between investors that trade CDS and similar investors that do not, and do not find evidence that investors change their behavior on the debt market at the onset of trading CDS.

Within investor, the probability to trade CDS increases with the reference entity's risk, as measured by its CDS spread, for all strategies and all sectors. These results hold controlling for bond and CDS liquidity. We also find evidence that banks, dealers, and to some extent investment funds, use CDS for rating arbitrage i.e., they trade more CDS on reference entities with high spreads conditional on a credit rating. This behavior may be driven by communication or regulatory incentives (Becker and Ivashina, 2015).[5]

Overall, CDS appear to have an ambiguous effect on the distribution of credit risk across investors. Investors might use CDS to hedge their most concentrated exposures. At the same time, the introduction of CDS increases the amount of exposures at default, allows investors to double up on their beliefs, and tilts the composition of credit risk outstanding towards riskier reference entities.

This paper contributes to three strands of the literature. First, we test theories from the literature on the determinants of risk management in general (Atkeson et al. (2015), Rampini and Viswanathan (2010)) and CDS trading in particular (Oehmke and Zawadowski, 2015; Che and Sethi, 2014; Sambalaibat, 2021). In this empirical literature, among others, Bai and Collin-Dufresne (2019) analyze the determinants of the CDS-bond basis, and Oehmke and Zawadowski (2017) study how CDS traders value their relative liquidity. Our paper is closest to recent contributions using granular data such as Jiang et al. (2021) who explore US mutual funds liquidity and risk-taking motives, Gündüz et al. (2017) who show that higher standardization of CDS fosters higher hedging by German banks, Czech (2021) who studies spillovers between the CDS and bond markets, or Boyarchenko et al. (2018) who investigate the determinants of trading in the CDS or in the bond markets.

Second, our paper speaks to the literature on CDS and risk-taking. A large literature analyzes the effects of CDS introduction on debt markets. Ashcraft and Santos (2009) show that being referenced in CDS contracts results in small spread declines for safe firms, but the opposite for riskier firms. CDS also allow firms to increase leverage (Hirtle, 2009), and extend maturities (Saretto and Tookes, 2013). Subrahmanyam et al. (2014) shows that this translates in an increase in borrower risk, while Danis and Gamba (2018) emphasize how CDS reduce the likelihood of out-of-court restructuring for distressed firms. Jiang et al. (2021) are to the best of our knowledge the only paper that studies how investors can use

[5] Article 122 of CRR prescribes rating-dependent risk weights for calculating capital requirements in the standard approach.

CDS to increase risk-taking, with a focus on US mutual funds. A number of papers finally exhibit evidence on rating arbitrage in the debt market (Becker and Ivashina, 2015; Choi and Kronlund, 2018; Boermans and van der Kroft, 2020), while Jiang et al. (2021) provide evidence on reach for yield in the CDS market.

To the best of our knowledge, our paper is finally the first to examine how single-name CDS affect the distribution of credit risk across investors, similarly to how Hoffmann et al. (2018) studied the effect of interest rate swaps on interest rate risk allocation across European banks, or how Hippert et al. (2019) studied the impact of index CDS on portfolio risk.

The rest of the paper is divided as follows. Section 2 presents our data. Section 3 discusses the methodology built to disentangle investor strategies by reference entity. Section 4 presents and discusses the effect of strategies on concentration, and Section 5 those on risk-taking. Section 5 concludes.

2. Data

2.1. Credit Default Swaps

Investors can choose between two families of instruments to gain credit risk exposure to a reference entity: debt or Credit Default Swaps (CDS). Unlike debt, the reference entity is not a counterparty to the CDS contract. CDS are derivative products where a buyer pays a premium, the CDS spread, to a seller, to insure a notional amount of reference debt until the maturity date of the contract. If the reference entity defaults before maturity, then the seller pays the buyer the notional times the recovery rate resulting from an auction on the defaulted bonds. Therefore, CDS are both insurance contracts designed to hedge credit risk, and synthetic debt instruments because the payoff to selling a CDS is akin to the one of buying a bond on margin.[6]

2.2. Data collection

Banque de France grants access to granular supervisory data on financial institutions. We collect quarterly data from 2016Q1 to 2021Q4 on investor credit risk holdings. The dataset includes three types of exposures: debt securities at the ISIN level, loans, and CDS. Two national registers, *OPC titres* and *Solvency 2*, report holdings of respectively French investment funds and French insurers, while *LIPPER* provides security holdings of all euro area (EA) open-ended investment funds. The *Securities Holding Statistics-Group (SHS-G)*

[6]Duffie (1999) or White (2014) provide detailed information on the valuation and pricing of CDS.

registry provides holdings of securities by EA banks. The scope of *SHS-G* data collection significantly increased in 2018Q3 to cover all banks directly supervised by the Single Supervisory Mechanism, and we only keep derivative positions of banks in quarters where they report their security holdings in SHS-G. Loans from French registered banks to NFCs are drawn from the French credit register. Finally, we use CDS data provided by the *Depository Trust & Clearing Corporation (DTCC)* to Banque de France under EMIR regulation. *DTCC* virtually includes all CDS contracts entered by a European Union (EU) counterparty. At the time of writing, the Banque de France access covered all positions of French investors, and of EU investors on French reference entities.[7] We uniquely identify investors and reference entities (issuers of securities and loans, and entities referencing CDS contracts) leveraging an enriched version of Eurosystem identification databases.[8] This identification database allows us to map the various entities or security identifiers to a unique entity identification code. We come back to our consolidation strategy in Section 2.3. We then aggregate quarterly exposures from investors to reference entities by instrument type.

We restrict our sample to investors trading at least one single-name CDS over the period, and to NFCs referencing CDS at least once. We drop exposures to financial and sovereign reference entities for which we do not have access to loan data. This allows us to focus on trading motives stemming from credit risk rather than counterparty risk. These latter would be more frequent if including reference entities belonging to the financial sector.[9] Similarly, we exclude index CDS to restrict the set of plausible CDS trading strategies. Index CDS can be used for instance for macro-hedging purposes, or for arbitraging baskets of single-name CDS. While index CDS are nowadays the most prevalent CDS instruments,[10] they represent smaller positions in our sample. As of 2019Q4, we observe €31 bn of net positions to NFCs through indices, to be compared with €54 bn in single-name CDS.[11] We also verify in Figure 2.7 in Appendix D that when investors hold index CDS positions, they mostly amplify single-name CDS positions, which suggests that single-name-index arbitrage remains a relatively small strategy in our sample.

Our dataset thus presents a near-exhaustive view of credit risk borne by investors on

[7] Appendix A.1 provides more details on the cleaning procedure for *DTCC* data.

[8] The *Register of Institutions and Affiliates Database (RIAD)* provides information on legal entities while the *Centralised Securities DataBase (CSDB)* references information on individual securities relevant for ESCB statistics. We enrich them with several complementary data sources: *GLEIF* for the Legal Entity Identifier (LEI), national registers on parent relationships between NFCs, and manually identify the largest remaining ISIN.

[9] See Gündüz (2018) for empirical evidence on counterparty risk mitigation using CDS.

[10] As of 2019Q2, single-name CDS represent $\sim$ \$0.5tn of net notional positions worldwide, versus $\sim$ \$1tn for indices (see ISDA (2019)).

[11] To calculate net positions to NFCs through indices, we break down index exposures into exposures to their components and filter out all non-NFC exposures.

NFCs for two perimeters: French investors on all NFCs, and EA banks and EA open-ended investment funds on French NFCs. We neglect non-French subsidiaries of French banks' loan exposures (not reported in the French credit register), as well as EA banks' cross-border lending to French NFCs, which is negligible compared to their holdings of debt securities.[12]

We enrich our exposure database with reference entity-level attributes. Reference entity ratings are collected from *CSDB* and *Solvency 2*. We retrieve time series of CDS spreads, CDS-bond basis,[13] and bond and CDS bid-ask spreads from *Refinitiv*, with a cleaning procedure described in Appendix A.3 to obtain a single time series for every reference entity. We also collect quarterly public CDS liquidity data on the top 1000 most traded reference entities from *DTCC*.[14] Finally, we add reference entity balance sheet data from the French register of firms *FIBEN*, and from *Eikon* and *Orbis* for respectively listed and non-listed non-French entities. Table 2.6 in Appendix E summarizes the key attributes of reference entities by rating. We also add investor-level attributes reported in the various holding datasets.

2.3. Our approach to consolidation

Banks and insurers are consolidated according to their prudential perimeters. CDS trading is generally undertaken at the group level, to manage risks arising from lending and investment activities at the legal entity level. Doing so, we remove intragroup holdings. We do not consolidate investors beyond prudential perimeters and thus do not observe risk management strategies for bank-insurance conglomerates. Even if they belong to the same conglomerate, banks and insurers are subject to different legal frameworks and consequently to separate reporting requirements and risk management strategies. Investment funds are left unconsolidated since risks are borne by fund share owners. Fund asset managers are exposed to funds performance through fees and commissions, but with limited liability.

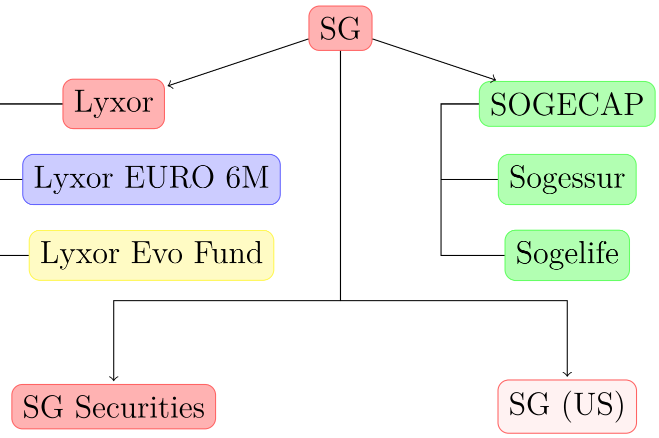
Figure 2.1 presents a stylised consolidation of Société Générale group. Banking subsidiaries are consolidated at the ultimate parent level, including any non-insurance fully owned subsidiary (the asset manager Lyxor). Insurers are consolidated at the insurance group level. Investment funds are left unconsolidated. The stylised conglomerate splits into 4 different investors: the bank Société Générale and its observed subsidiaries, the insurer SOGECAP, and two investment funds, Lyxor EURO 6M and Lyxor Evo Fund.

Reference entities are consolidated at their highest level of consolidation since CDS generally reference the ultimate parent while debt can be issued at all levels of the group. Financial

[12] As of end-2019, cross-border lending represents 7% of loans to French NFCs in national accounts.

[13] The CDS bond basis is defined as the difference between the CDS and the asset swap spread at a corresponding maturity.

[14] `https://www.dtcc.com/repository-otc-data`.



Notes: One color corresponds to one investor in our sample. Bank affiliated entities for which we have all credit risk exposures are filled in red. We miss loan exposures from non-French subsidiaries in light red. Insurers affiliated entities are in green. Funds are kept unconsolidated.

Fig. 2.1. Stylised consolidation for Société Générale

institutions belonging to non-financial corporations are excluded. This approach gives an exact view on credit risk exposure if default risk fully correlates within a reference entity group. However, limited liability clauses within a group may still distort our observation of real exposures.

2.4. Sample overview

Table 2.1 presents the number of investors and reference entities in the pooled sample, and their size averaged across periods. By convention and throughout the paper, long exposures on credit risk (hold debt, sell CDS) are positive figures, while short exposures (short-sell debt, buy CDS) are negative.

Category	#Obs	CDS sell	CDS buy	#CDS sell	#CDS buy	Bonds long	Bonds short	Loans	%CDS Long
Bank	21	6.80	-2.55	426.07	156.64	16.04	-0.07	51.88	0.09
Dealer	4	23.29	-13.30	747.71	476.71	18.20	-1.10	67.58	0.21
Fund	513	5.29	-1.62	457.07	272.93	30.93	-0	0	0.15
Insurer	4	1.30	-0.05	51.79	6.29	67.11	0	0	0.02
NFC FR	73	7	-4.11	470.71	291.21	39.33	-0.30	117.55	0.04
NFC NFR	991	29.68	-13.41	1,211.93	621.36	92.95	-0.87	1.91	0.24
All	28307	36.68	-17.52	1682.64	912.57	132.28	-1.17	119.46	0.13

Notes: *#Obs* is the number of distinct observations in the pooled strictly post-2018Q2 sample. For the total, it corresponds to the total number of investor-reference entity pairs. *#CDS sell* and *#CDS buy* are the average number of positions by period. Other statistics correspond to pooled average net exposures by investor and reference sector x region, in €billion. *%CDS Long* is the share of long credit risk that CDS sold represent.

Table 2.1: Descriptive statistics

Our sample includes 513 investment funds (132 French and 381 non-French), 21 EA banks

(2 French and 19 non-French), 4 French insurers, and 4 dealers (3 French and 1 non-French). We split dealers from banks if the head of the banking group is included in the G16 list of derivative dealers.[15] Dealers account for the lion's share of CDS positions. They sell (buy) on average €23 bn (13) single-name CDS, compared to €5 bn (2) for funds, €7 bn (3) for banks, and €1 bn (0.05) for insurers. Banks and dealers lend on average €119 bn to NFCs, almost exclusively to French borrowers.[16] Total average bond exposures stand at €132 bn, of which insurers hold around half. CDS trade on respectively 73 and 991 French and non-French firms. We observe a total of 28,307 investor-reference entity pairs over our sample. Figure 2.8 in Appendix D displays net exposures to credit risk for French and non-French reference entities by instrument type (loans, bonds, CDS) and sector as of 2019Q4.

Although single-name CDS represent a small fraction of aggregate credit risk exposures, their contribution to exposures to large firms whose idiosyncratic shocks may matter for aggregate outcomes is important. For instance, as evident from the last column of Table 2.1, CDS represent 21% of total credit risk exposures to CDS-referenced firms for dealers in our sample. Figure 2.9 in Appendix D plots the distribution of the share of CDS in investor exposures. CDS appear to represent small shares of total debt exposures, with the exception of some investment funds. However, they can represent important shares of exposures to NFCs referenced as CDS, and generally represent the bulk of short credit risk exposures.

3. A methodology to disentangle strategies

3.1. Description of the methodology

CDS trading motives can be broadly grouped into three categories.

Investors can purchase CDS for hedging to downsize certain credit risk exposures. This occurs in two situations. First, investors may want to adjust exposures in response to a shock affecting the reference entity, their beliefs about the reference entity, or their ability to bear associated risks. In Atkeson et al. (2015), investors purchase derivatives to share aggregate risk, while bond holders become hedgers after revising their beliefs in Sambalaibat (2021) model. Both cases feature investors which inherit legacy assets and subsequently purchase derivatives. Second, banks may want to maintain a valuable lending relationship and extend lending to one of their clients, while not being able to bear the associated risks. This motive corresponds to the textbook case of J.P. Morgan's first CDS purchase on Exxon during the

[15] The group of the sixteen largest derivatives dealers (G16) includes Bank of America, Barclays, BNP Paribas, Citigroup, Crédit Agricole, Credit Suisse, Deutsche Bank, Goldman Sachs, HSBC, JP Morgan Chase, Morgan Stanley, Nomura, Royal Bank of Scotland, Société Générale, UBS, and Wells Fargo.

[16] There is a small residual of cross-border lending to non-French borrowers.

1989 oil spill, which allowed them to support Exxon with a large credit line.

Investors also trade CDS for speculative purposes, in particular since CDS buyers are not required to hold the underlying debt.[17] In that respect, CDS are an alternative trading venue for credit risk investment. Non-redundancy with debt has been the focus of several contributions. Oehmke and Zawadowski (2015) highlight the liquidity advantage of CDS, arguing they are a more standardized product, with smaller inventory costs and price-impacts of trading. Che and Sethi (2014) or Garleanu and Pedersen (2011) contend that leverage constraints are looser for selling CDS than for purchasing bonds on margin. Jiang et al. (2021) discuss the opacity advantage of CDS attributable to their smaller market value (null at inception) and their off-balance sheet reporting.

A last trading motive arises from the coexistence of debt and CDS. Borrowing at the risk-free rate and purchasing debt should yield the same payoff as selling a CDS referencing that debt with the same maturity. In practice, market imperfections give rise to the CDS-bond basis, the spread difference between the two strategies. Bai and Collin-Dufresne (2019) extensively discuss this arbitrage opportunity.

Our methodology aims at disentangling these three trading strategies by exploiting the relative sign, nature, and timing of matched debt and CDS positions at the investor-reference entity-quarter level. A trading strategy for CDS_{ijt} is defined as the reason why an investor i holds a CDS on reference entity j at quarter t.

Investors who do not hold CDS on a reference entity are *standard* investors. Among investors holding CDS, we first examine whether debt and CDS exposures (weakly) amplify or (strictly) offset each other. Investors are *speculators* when CDS and debt amplify each other. Speculators may be *naked* if investors hold no underlying debt on the reference entity.

Among investors with offsetting debt and CDS exposures, we first single out positions whose hedging ratio, the ratio of the CDS notional over the debt exposure $\frac{CDS_{ijt}}{Debt_{ijt}}$, is below -1.2. These investors are *naked speculators* since most of the CDS creates a negative net position rather than offsets existing debt. Among remaining positions, we split *hedgers* from *arbitrageurs* using the aforementioned definition of hedging. Hedgers are investors entering a CDS position when already holding the underlying debt (hedging occurs in response to a shock), or acquiring simultaneously both positions if at least part of the debt is a loan (hedging occurs to maintain a lending relationship). Conversely, arbitrageurs simultaneously acquire offsetting CDS and bonds.[18]

[17] Since 2011 and the unfolding of the euro sovereign crisis, the Regulation on Short Selling bans purchasing CDS on euro area sovereigns when the purchaser does not hold the underlying debt. However this does not extend to non-financial corporations.

[18] Doing so, we might understate the amount of hedging at the expense of arbitrage if shocks to which investors respond by buying CDS happen within a quarter. However, the limited number of arbitrageurs we

Finally, when entry is not observed because the CDS exposure is already observed at 2016$Q1$, we exploit exit patterns and relative hedging ratios for identification. The latter is required since investors hedging bonds in response to shocks may not be distinct from arbitrageurs if they exit simultaneously in bond and CDS. We posit that hedgers exit either first in CDS, or simultaneously in debt and CDS with part of the debt being a loan, or simultaneously in debt and CDS with a hedging ratio more likely to be that of a hedger. Arbitrageurs on the other side exit simultaneously in bond and CDS and exhibit a hedging ratio more likely to be that of an arbitrageur. In practice, we find that all but one hedging exposure are related to maintaining a lending relationship.

Our strategy leaves us with a number of other strategies which correspond to positions for which entry and exit are unobserved, or follow non-interpretable patterns. More details on the methodology can be found in Appendix B.

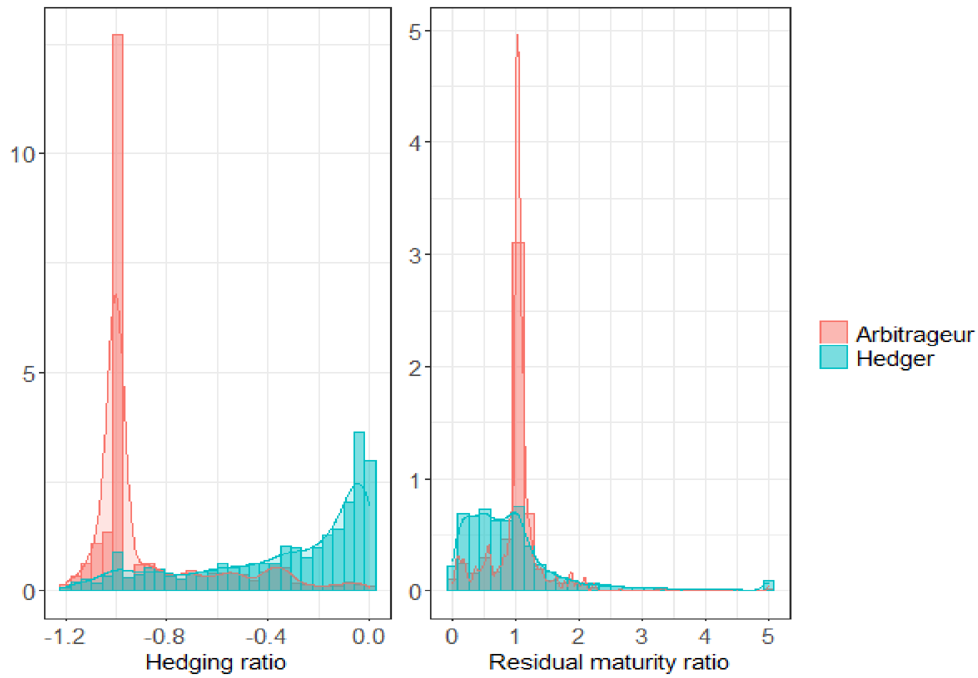
3.2. Hedgers vs Arbitrageurs

Disentangling hedgers from arbitrageurs crucially relies on the timing of entries and exits. To assess whether this approach allows separating strategies of a different nature, we examine the distribution of two statistics. Figure 2.2 represents the pooled distribution of each strategy's hedging ratio (on the left-hand side), and residual maturity ratio (on the right-hand side).[19] As expected, the hedging ratio distribution of arbitrageurs exhibits a clear mode around -1 (resp. 1 for the residual maturity ratio). This reflects the vanilla arbitrage strategy, which consists of buying a bond on margin and covering its face value with a CDS of identical notional. In contrast, the median hedging ratio of hedgers stands at 22% (see Table 2.8 in Appendix B). Similarly, the mean residual maturity ratio of arbitrageurs appears close to 1, while that of hedgers is closer to 0.5.

Another salient feature of the difference between CDS purchased by hedgers and arbitrageurs is the CDS-bond basis. As discussed in Bai and Collin-Dufresne (2019), the negative basis prices four risks: bond collateral value variation, bond liquidity risk, investor funding risk, and counterparty risk in the CDS market. Assuming arbitrageurs have a relative advantage in managing those risks, the more negative the basis, the more profitable the arbitrage strategy. We formally test whether CDS subject to arbitrage strategies exhibit a different basis by estimating Equation (2.1):

observe make us confident this bias is limited.

[19] Residual maturities are a notional-weighted average of residual maturities of all exposures consolidated at the investor-reference entity-quarter level.



Notes: Distributions before the identification of offsetters already existing as of 2016Q1 (step 4 of the methodology described in Appendix B). By convention, purchasing a CDS gives rise to a negative CDS position hence the negative hedging ratio. The residual maturity is the average maturity for the investor-reference entity holdings weighted by debt holdings or CDS positions.

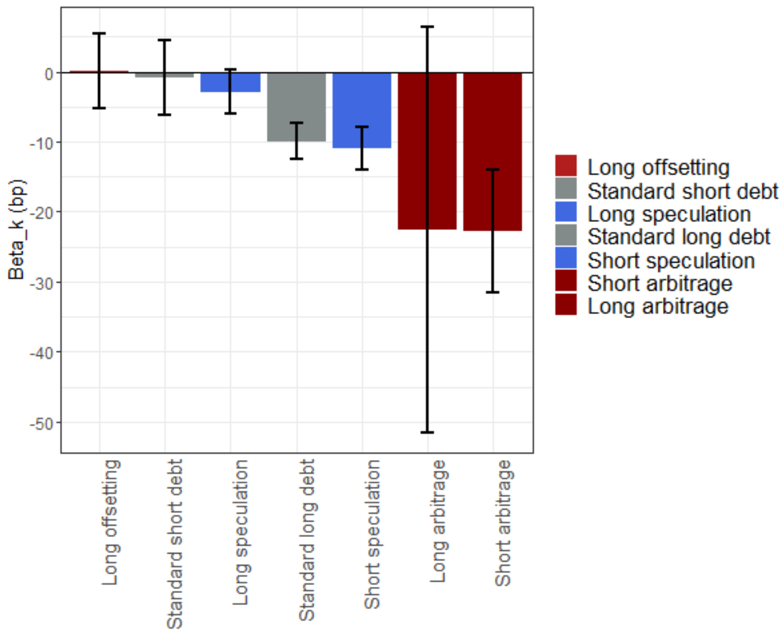
Fig. 2.2. Pooled distribution of hedging ratios (lhs) and residual maturity ratios (rhs) for hedgers and arbitrageurs purchasing CDS

$$CDSBondBasis_{ijt} = \alpha Spread_{jt} + \sum_k \beta_k Strategy_{ijt}^k + FE_{it} + \epsilon_{ijt}, \tag{2.1}$$

with $Spread_{jt}$ the reference entity CDS spread to control for credit risk, and FE_{it} investor-quarter fixed effects. Figure 2.3 plots the coefficients associated with each strategy, relative to non-arbitrage short offsetting strategies. Table 2.7 in Appendix E provides the econometric estimates and shows that these results also hold controlling for bond and CDS liquidity.

Arbitrage strategies combining a CDS and a bond purchase (*short arbitrage*) involve CDS with a basis 18 bps lower than in other offsetting strategies involving the purchase of a CDS. Short arbitrage also relates to CDS-bond bases which are significantly lower than any other strategy.

Taken together, these analyses make us confident that hedgers and arbitrageurs have different trading motives that we capture efficiently with our methodology.



Notes: Bars represent 90% confidence interval. Standard errors are clustered at the investor-quarter level. By convention, short strategies involve buying CDS, and long strategies selling CDS. Speculators include naked speculators. *Long offsetting* includes offsetting positions with long CDS and short debt which are not long arbitrageurs. CDS-bond basis are winsorized at the 1% level on each side.

Fig. 2.3. Mean CDS-bond basis by strategy relative to short offsetters excluding short arbitrageurs

3.3. Trading strategies in the sample

Figure 2.4 plots the shares and notional amounts of strategies by investment sector.[20] Overall, dealers represent the bulk of exposures with 72% of positions in notional (resp. 52% of CDS positions in number). Investment funds represent 13% of the notional (resp. 29% of positions) with the largest share of naked speculators, and banks account for 13% of the notional (resp. 18% of positions) and the largest share of hedgers. Arbitrage is a minor activity in terms of holdings, and is essentially undertaken by investment funds and banks.[21] Insurers' participation in the single-name CDS market for NFCs is anecdotal. Figure 2.10 in Appendix D presents the evolution of those strategies over time.

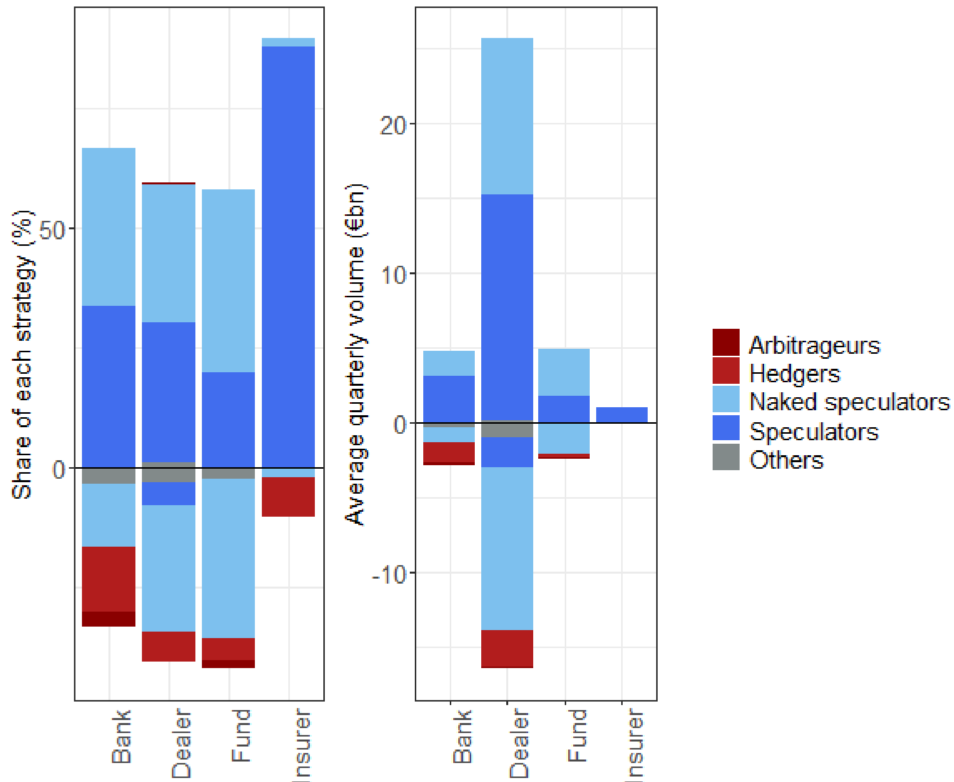
Descriptive statistics by strategy can be found in Table 2.8 in Appendix E. They point

[20]Our results are in line with Jiang et al. (2021) although they focus on US mutual funds. They find that 59% of investment funds are long speculators, 17% short naked speculators, and 23% offsetters. In our pooled dataset, 67% are long speculators including naked (62% when including non-funds), 28% of funds are short speculators including naked speculators (resp. 25%), and 5% are offsetters (resp. 13%).

[21]It is likely that arbitrage represents a larger share of *transactions*, if arbitrage positions are opened and closed within a quarter as investors undo the arbitrage opportunity. Our approach tells us that arbitrage do not represent significant *positions* for investors at a point in time.

to other differences between strategies. For instance, arbitrageurs exhibit a similar turnover for debt and CDS positions, while hedgers exhibit the highest CDS turnover - consistent with the idea that they use them to adjust credit risk exposures in response to shocks.

Over the following sections of the paper, we focus on the three main strategies identified with our methodology: long speculators, short speculators, and hedgers.



Notes: Strategy shares correspond to the share of each strategy in absolute notional CDS exposure by investor sector, with negative values corresponding to short CDS positions.

Fig. 2.4. Pooled share (lhs) and average volume (rhs) of strategies by sector

3.4. CDS effect on total exposures at default

The except for banks, the majority of CDS purchased do not offset preexisting debt exposures. The share of offsetting CDS purchases stands at 65% for banks, 17% for funds, and 22% for dealers. In the aggregate, 27% of purchased CDS offset preexisting debt exposures and 73% do not. As shown in Figure 2.10 in Appendix D, these figures are relatively stable over time and the variation in net positions is essentially driven by speculation. Since CDS selling barely offsets any short-selling position, this implies that CDS trades are associated with an increase in total credit risk exposures outstanding. This increase would be worth 73% of the net value of CDS positions if we observed all counterparties of CDS purchasers in

our sample's. The value of total credit risk exposures outstanding matters, if only because it corresponds to the concept of "exposures at default" (EAD) in bank capital regulation i.e., the maximum amount that an investor may lose in case of reference entity default.

More formally, we calculate how CDS change total exposures at default as follows:

$$\Delta EAD_t = \left(\Sigma_{ij} max(Debt^+_{ijt} + CDS^-_{ijt}, 0) + max(Debt^-_{ijt} + CDS^+_{ijt}, 0)\right) / Debt^+_{ijt} - 1, \quad (2.2)$$

where superscripts denote the sign of the positions using the convention that long credit risk exposures are positive. We plot ΔEAD_t in Figure 2.5. Graphically, we see that accounting for CDS leads to an increase of EAD standing between 10 and 15% of total preexisting debt exposures, a share which has been relatively stable since mid-2019.

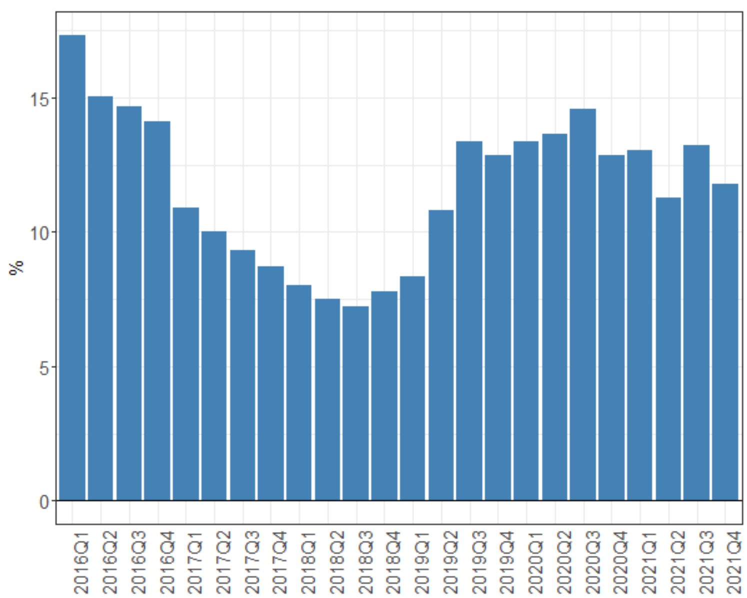


Fig. 2.5. Percentage increase in total exposures at default when accounting for CDS

4. Portfolio concentration

4.1. Identification strategy

According to Atkeson et al. (2015), risk-sharing motives increase investors' incentives to hedge their largest exposures, while the fixed cost of hedging prevents them to do so for small exposures in value.[22] In contrast, two alternate views emerge from the literature on specu-

[22] This fixed cost of hedging originates in the legal expenses paid to create a trading desk and to connect to market infrastructures needed for contract payments.

lators. First, investors could substitute debt with CDS. This result hinges on risk-sharing motives: investors with a low endowment in the underlying asset sell CDS to increase their risky exposure. It also stems from differences in investors' liquidity preferences. Conditional on having sufficiently strong beliefs, Oehmke and Zawadowski (2015) speculators sell CDS instead of holding debt to benefit from higher liquidity in the CDS market. Second, investors could use CDS to complement their existing debt exposures. In Che and Sethi (2014) view, speculators sell CDS to take synthetic leverage on reference entities on which they are optimistic, taking advantage of relatively low margin requirements. To test these predictions, we estimate how the share of debt exposure affects the likelihood of adopting hedging and speculative strategies in a discrete choice model.

There are two major hurdles in identifying the causal effect of debt concentration on the likelihood of adopting a strategy. First, trading CDS may induce the reference entity to issue more debt (Saretto and Tookes, 2013), thereby increasing the concentration of debt exposures on this reference. We circumvent this issue by considering only references with CDS traded on their name. We also control for reference entities gross debt in the regressions to account for size effects.

Second, both CDS trading and debt concentration might be jointly determined by the investor in the first place. Hedgers could purchase additional debt on a given reference entity knowing they can buy CDS to shed off this debt in the future (Sambalaibat, 2021). Conversely, speculators could choose to hold less debt if they have the ability to sell CDS on the same reference entity. Therefore, estimating the effect of debt concentration on the propensity to trade CDS may lead to upward biased estimates for hedgers, and downward biased estimates for long speculators.

To address this issue and identify the causal effect of debt concentration on trading strategies, we instrument debt shares at the investor-reference entity level by the share of the reference entity's gross debt in the universe $\mathcal{U}_i$ of reference entities ever held by the same investor. As already discussed, reference entity gross debt could increase with CDS trading. However, since we focus on a subsample of entities which all reference CDS at least once, we posit their propensity to issue additional debt due to CDS trading are similar. The choice by investors to include a reference entity in their debt investment universe $\mathcal{U}_i$ may also be jointly determined with CDS positions. Investors may decide not to hold debt at all, knowing they can gain long speculation positions by selling CDS only. We will treat the case of those naked speculators separately, and focus initially only on investors which hold some strictly positive amount of debt.

Table 2.9 in Appendix E provides some summary statistics for the distribution of strictly positive debt shares across investor sectors and trading strategies. Hedgers display higher

debt shares than standard long debt investors for all sectors. Perhaps surprisingly, long speculators also display higher debt shares than standard investors - although the difference is smaller.

Using a two-stage least squares type of estimation would produce inconsistent estimates of the coefficients in the non linear discrete choice model we use. We resort to the control function approach described by Wooldridge (2015) among others.[23] The method proceeds in two stages. In the first stage, we regress the endogenous variable, the debt share, on the instrument and the exogenous variables. The fitted residuals from the first stage are called the control function. They include the potentially endogenous component of debt shares, the one which is not explained by the instrument nor the exogenous variables. The second stage then adds the control function to the logistic model along with the endogenous and exogenous variables.

The first stage writes:

$$\frac{Debt_{ijt}}{TotExp_{it}} = \gamma \frac{GrossDebt_{jt}}{\sum_{k \in \mathcal{U}_i} GrossDebt_{kt}} + \Pi_1 X_{jt} + FE_{it} + \nu_{ijt}. \tag{2.3}$$

The endogenous variable $\frac{Debt_{ijt}}{TotExp_{it}}$ measures the debt share i.e., the share of investor i exposure to reference entity j in quarter t, as a percentage of i total debt exposures. The instrument $\frac{GrossDebt_{jt}}{\sum_{k \in \mathcal{U}_i} GrossDebt_{kt}}$ measures the share of reference entity j gross debt in the universe of reference entities $\mathcal{U}_i$ ever held by investor i. FE_{it} are investor-quarter fixed effects, controlling for investors' time-varying demand for risk. We add a set of reference entity controls X_{jt} which also explain the likelihood of trading CDS. Investors might trade more CDS on larger reference entities because of economies of scale (larger outstanding amounts of debt, higher bond and CDS liquidity). We control for reference entity gross debt in logarithm to address this concern. We add reference entity CDS spread and Credit Quality Step (CQS) to control for the reference entity riskiness.[24] We also add CDS bid-ask spreads to control for CDS liquidity and the ability of investors to easily enter into a strategy. Finally, we add a dummy for French reference entities.

The second stage logistic model writes:

$$Y_{ijt} = \Lambda \left(\beta \frac{Debt_{ijt}}{TotExp_{it}} + \Pi_2 X_{jt} + \delta \hat{\nu}_{ijt} + FE_{it} \right) + \epsilon_{ijt} \tag{2.4}$$

where Y_{ijt} is a dummy for CDS trading strategies like speculating or hedging. Following

[23]See Petrin and Train (2010) for an application to a logistic model of consumer choice.

[24]Credit Quality Steps are a mapping from rating agency ratings into larger rating buckets, as set by the European Banking Authority. CQS are used inter alia to determine eligibility for central bank operations in the EA.

the control function approach, we add the fitted residuals $\hat{\nu}_{ijt}$ from stage one. If hedgers, we would expect β to be positive if they shed off their most concentrated exposures. For speculators, if CDS are a complement (resp. a substitute) for debt, then β is positive (resp. negative).

Errors might be correlated across investors and reference entities. Therefore, we cluster standard errors at the investor-quarter and reference entity-quarter levels. In addition, we correct our estimates for the incidental parameter bias that arises in non-linear models with fixed effects, using the method developed in Fernández-Val and Weidner (2016). Since the control function ν_{ijt} is estimated separately in the first stage, we implement a pair cluster bootstrap-t procedure presented in Appendix C to derive confidence intervals for β. In a nutshell, the bootstrap iterates by drawing clusters at the reference entity-quarter level with replacement. For each iteration, the algorithm estimates the two stage model and tests the null hypothesis of the coefficients being different from the original estimates. The algorithm retrieves a distribution of t-statistics to compute bootstrap-t confidence intervals for the coefficient estimates. We report robust Kleibergen-Paap F-statistics (Kleibergen and Paap, 2006) from the first stage regression and verify they are above the threshold of 10 to reject weak instrument concerns.

4.2. Main results

Table 2.10 in Appendix E presents the first-stage results on the sample of investors being strictly long on their reference entity's debt. The instrument positively relates to debt shares for all sectors. It stands at respectively 0.53 for banks, 0.41 for dealers, and 0.19 for funds. Furthermore, Kleibergen-Paap F-statistics are sufficiently large for every specification.

Table 2.2 presents the likelihood to adopt hedging strategies by sector. As expected, banks and dealers offset their most concentrated exposures more. On average, the probability of hedging increases by around 31pp for banks and 113pp for dealers when debt shares increase by 1pp. These effects are particular large, even when considering that debt shares are typically small (see Table 2.9 in Appendix E for summary statistics on debt shares by sector and strategy). The coefficient is not significant for investment funds. These results are consistent with the fixed cost of hedging and risk-sharing argument, but also with the empirical results of Gündüz et al. (2017), who find that German banks increased hedging on larger and riskier exposures after the CDS "Small Bang". Our analysis corroborates these results for a larger set of financial institutions and emphasizes how debt concentration is an important driver of hedging.

Table 2.3 turns to the likelihood of adopting long speculating strategies by sector condi-

	P(Hedger)		
	Bank	Dealer	Fund
	(1)	(2)	(3)
Debt share	3.51^{*}	12.87^{*}	-0.88
	$[1.27; 5.56]$	$[7.72; 18.16]$	$[-2.56; 0.29]$
Log Gross debt Ref	0.04	-0.08^{*}	0.21^{*}
	$[-0.02; 0.10]$	$[-0.15; -0.03]$	$[0.14; 0.29]$
Spread Ref	-0.19^{*}	-0.05^{*}	0.01
	$[-0.25; -0.13]$	$[-0.09; -0.02]$	$[-0.03; 0.08]$
CDS bid-ask spread Ref	-0.21	-0.46	-6.54^{*}
	$[-0.78; 0.43]$	$[-1.10; 0.27]$	$[-8.51; -4.57]$
FR Ref	-0.36	-0.80	0.38^{*}
	$[-1.05; 0.37]$	$[-2.07; 0.38]$	$[0.16; 0.64]$
CQS Ref	0.52^{*}	0.38^{*}	0.30^{*}
	$[0.44; 0.61]$	$[0.30; 0.47]$	$[0.16; 0.41]$
First stage residuals	-1.34	-9.17^{*}	2.19^{*}
	$[-3.32; 0.91]$	$[-14.95; -4.03]$	$[0.95; 3.87]$
Kleibergen-Paap Wald test	181.07	151.65	277.83
First-stage coefficient	0.53	0.41	0.19
Inv x Quarter FE	Y	Y	Y
IBP correction	Y	Y	Y
APE	0.31	1.13	-0.01
Num. obs.	9292	13016	14316

Notes: Estimation of Equation (2.4) for hedgers. The sample includes all strictly positive debt positions. *Debt share* is right-winsorized at 2.5%. CDS spreads are right-winsorized at 1% and CDS bid-ask spreads are winsorized at 0.5% on both sides. Spreads are expressed in percentage points. *CQS Ref* is the Credit Quality Step of the reference entity expressed in units, with higher units referring to higher risk of default. Coefficients are corrected from the incidental parameter bias using the methodology developed by Fernández-Val and Weidner (2016). *APE* designates the average marginal effect (in points) of the debt share (in percentage points) over the sample. Standard errors are clustered at the investor-quarter and reference entity-quarter level. We present bootstrap confidence intervals at the 5% level, superscripts * indicate that the null is rejected at this threshold.

Table 2.2: Probability to hedge and debt exposure concentration

tional on holding the reference entity debt. Debt shares also positively relate to the likelihood of selling CDS for banks and investment funds. On average, the probability of speculating increases by around 103pp for banks and 6pp for funds when debt shares increase by 1pp. The coefficient of interest is not significant and close to zero for dealers, suggesting that these investors do not initiate trades, but rather mirror to banks' and investment funds demand for hedging and short speculation. Conditional on holding the reference entity debt, investors sell CDS as a complement rather than a substitute.

	P(Long Speculator)		
	Bank	Dealer	Fund
	(1)	(2)	(3)
Debt share	7.29*	0.39	2.16*
	[5.33; 9.37]	[−2.60; 3.40]	[1.22; 2.96]
Log Gross debt Ref	0.05	0.01	−0.03
	[−0.01; 0.11]	[−0.02; 0.05]	[−0.11; 0.04]
Spread Ref	−0.02	0.01	0.12*
	[−0.07; 0.04]	[−0.01; 0.04]	[0.08; 0.16]
CDS bid-ask spread Ref	−4.43*	−3.16*	−5.96*
	[−5.61; −3.26]	[−3.73; −2.63]	[−7.28; −4.87]
FR Ref	−1.86*	−0.10	0.43*
	[−2.59; −1.18]	[−0.81; 0.57]	[0.32; 0.57]
CQS Ref	0.15*	−0.05	0.04
	[0.04; 0.24]	[−0.11; 0.01]	[−0.02; 0.14]
First stage residuals	−6.92*	−1.53	−1.98*
	[−8.98; −4.99]	[−4.55; 1.38]	[−2.77; −1.03]
Kleibergen-Paap Wald test	181.07	151.65	277.83
First-stage coefficient	0.53	0.41	0.19
Inv x Quarter FE	Y	Y	Y
IBP correction	Y	Y	Y
APE	1.03	0.08	0.06
Num. obs.	10625	13059	35956

Notes: Estimation of Equation (2.4) for long speculators. The sample includes all strictly positive debt positions. *Debt share* is right-winsorized at 2.5%. CDS spreads are right-winsorized at 1% and CDS bid-ask spreads are winsorized at 0.5% on both sides. Spreads are expressed in percentage points. *CQS Ref* is the Credit Quality Step of the reference entity expressed in units, with higher units referring to higher risk of default. Coefficients are corrected from the incidental parameter bias using the methodology developed by Fernández-Val and Weidner (2016). *APE* designates the average marginal effect (in points) of the debt share (in percentage points) over the sample. Standard errors are clustered at the investor-quarter and reference entity-quarter level. We present bootstrap confidence intervals at the 5% level, superscripts * indicate that the null is rejected at this threshold.

Table 2.3: Probability of long speculation and debt exposure concentration

These results corroborate Che and Sethi (2014) view: investors sell CDS to drive up

their exposure to a given reference entity. In contrast, the risk-sharing argument from Atkeson et al. (2015) and the liquidity preference theory from Oehmke and Zawadowski (2015) do not seem to drive the choice of CDS relative to debt exposures. Our results also differ from those of Acharya et al. (2022), who showed how German banks less exposed to peripheral European sovereigns increased CDS selling most throughout the European sovereign debt crisis. The first stage residuals i.e., the control function, all negatively relate to the probability to adopt a speculating strategy. This is consistent with the direction of the bias we emphasized previously: long speculators choose to hold smaller debt exposures knowing they can complement these exposures by selling CDS.

We extend the analysis to long naked speculators. By definition, CDS are a substitute to individual debt exposures in these strategies. However, CDS may still be used as complements when aggregating exposures at a higher level. To test this, we aggregate exposures at the country-rating level and re-estimate the two stages model using country-rating debt concentration as the key variable of interest. Results are housed in Table 2.11 in Appendix E. Banks and dealers engage more in long naked speculating strategies when they hold larger shares of the same country-rating reference entities in their debt portfolio. On average, the probability of being a long naked speculator increases by around 12pp for banks and 97pp for dealers when the share of debt exposure increases by 1pp. The coefficient is not significant for investment funds. Again, this result validates the intuition of Che and Sethi (2014): banks and dealers sell more naked CDS to leverage on their specialisation, and complement the debt they hold at the country-rating level.

5. CDS and risk-taking

5.1. Main result

There are four main reasons why demand for CDS may vary with credit risk. First, disagreement between investors may increase with reference entity risk (Oehmke and Zawadowski, 2017). Second, demand for hedging may relate to reference entity risk: in Atkeson et al. (2015), incentives for risk management increase with the level of risk to be shared. Third, CDS bear a margin advantage relative to debt which increases for riskier reference entities. As Darst and Refayet (2018) note from FINRA,[25] initial margins required to purchase an investment grade (100 bps spread) bond on margin are 10% of the purchase market value. This compares to 4% of the notional to sell a CDS with the same spread at a 5

[25] FINRA 4210 and 4240 rule-books on initial margins are available here `https://www.finra.org/rules-guidance/rulebooks/finra-rules`.

year maturity. The difference rises when rating deteriorates: the initial margin required to purchase a non-listed high-yield bond on margin amounts to 50% of its market value whereas it stands at 25% of the notional to sell a 700 bps CDS spread with 5 years maturity. Fourth, Jiang et al. (2021) argue that CDS are more opaque and provide incentives for risk taking. They provide two rationales for this which may also apply in our setting: CDS are not processed in regular holdings database and CDS contracts are often initiated at close to zero market value and therefore do not immediately affect risk metrics.[26]

In this section, we seek to understand how CDS trading strategies relates to CDS spreads. As for credit risk concentration, risk-taking using CDS may be endogenous to CDS trading. Investors may decide to reduce their demand for risky debt when they start selling CDS. In the absence of an adequate instrument for reference entity risk, we instead extend our dataset to include the 3,000 largest debt holders never trading CDS as a control group, to show that investors entering or exiting the CDS market do not simultaneously change the riskiness of their debt portfolios.

We remove investor-quarters which hold less than 5 debt exposures with identified CDS spreads. Our sample then contains 66 investors always trading CDS (15 banks, 4 dealers, and 47 funds), 937 never trading CDS (17 banks and 920 funds), 37 investors entering (only funds), and 38 exiting (2 banks and 36 funds) the CDS market. 167 investors (only funds) start and stop trading CDS during the period, and are also dropped from our exercise.

We test the relation between investors' debt portfolio riskiness and CDS trading. To do so, we estimate a staggered difference-in-difference model as follows:

$$MeanDebtSpread_{it} = \beta \mathbb{1}\{\text{CDS trading}_{it}\} + \gamma log(\sum_j |Debt_{ijt}|) + FE_i + FE_t + \epsilon_{it}, \quad (2.5)$$

where $MeanDebtSpread_{it}$ designates the mean spread of the debt instruments held by investor i at quarter t, and $\mathbb{1}\{\text{CDS trading}_{it}\}$ a dummy if investor i trades CDS at time t. FE_i is an investor-level fixed-effect, and FE_t a time fixed-effect. Importantly, in such a setup where the treatment $\mathbb{1}\{\text{CDS trading}_{it}\}$ is staggered over time, β will provide an unbiased estimate of the average treatment effect of trading CDS under the assumption that treatment effects are homogeneous over time (see for instance De Chaisemartin and D'Haultfoeuille (2022)). In other words, we make the assumption that if anything, investors adjust the riskiness of their debt portfolio in the very period they start trading CDS, and

[26] Their final point is specific to the US market and outdated, being that before 2012 (when the SEC specified the rules for cash collateral segregation for CDS short positions), there was no clear metric to gauge the level of CDS-induced leverage.

not further in subsequent periods.

The estimation is run on four sub-samples. Columns (1) and (2) of Table 2.4 consider the case of long speculators, and estimate the change in mean debt spread of long speculation exposures upon entering (1) or exiting (2) the CDS market. Symmetrically, columns (3) and (4) consider the case of short hedgers. There are not enough debt short-selling exposures in our dataset to also test whether investors reduce the riskiness of their debt portfolio upon starting to trade CDS. We distinguish short hedgers from long speculators since the bias could take opposite signs for both strategies. Hedgers may increase the riskiness of their debt portfolio upon starting to hedge, while speculators could in contrast reduce it. The results presented in Table 2.4 show that CDS trading does not relate significantly to debt riskiness.[27]

	Long Speculators		Short Hedgers	
	Entry	Exit	Entry	Exit
	(1)	(2)	(3)	(4)
CDS trading	19.26	5.21	9.47	4.35
	(13.87)	(4.88)	(13.81)	(5.33)
Log Total Exp	0.77	-0.83	0.14	-1.01^{*}
	(2.31)	(0.60)	(2.28)	(0.61)
Quarter FE	Y	Y	Y	Y
Investor FE	Y	Y	Y	Y
Adj. R^2	0.83	0.77	0.82	0.67
Num. obs.	3637	1518	3637	1511

Notes: Estimation results from Equation (2.5). Dependent variables are investors' debt-only mean spreads, expressed in basis points. Debt spreads are right-winsorized at 1% before being aggregated at the investor level. *CDS trading* is a dummy taking value 1 if the investor is trading at least a CDS in a given period. *Log Total Exp* corresponds to the log of the total absolute value of investors' debt exposures. Columns (1) and (3) (entry) contain all investors never trading CDS, or beginning to trade CDS in the sample. Columns (2) and (4) contain all investors always trading CDS or exiting CDS trading in the sample. Long speculators have strictly positive debt exposures associated to weakly positive CDS selling positions. Short hedgers have strictly positive debt exposures associated to no CDS or hedging positions as per our methodology. Insurers, and investor-quarters with less than 5 debt exposures with observable CDS spreads in any period are excluded from the sample. Standard errors are clustered at the investor level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 2.4: Effect of CDS trading on investor-level debt spreads

We now turn to the main test of the section. We seek to estimate whether the probability to trade CDS increases with reference entity risk. We estimate the following logistic equation:

[27] A positive and significant coefficient for long speculators would imply that our finding that investors use CDS for additional risk-taking is conservative. Conversely, a positive and significant coefficient for short offsetters could potentially nullify our result that CDS allow investors to hedge their riskiest exposures.

$$\mathbb{P}(CDS \neq 0)_{ijt} = \Lambda\Big(\beta_{S_i} Spread_{jt} + \Pi X_{ijt} + FE_{it}\Big) + \epsilon_{ijt}, \tag{2.6}$$

where our main coefficients of interest is the sector-level β_{S_i}. X_{ijt} includes reference entity-level controls including bond and CDS measures of liquidity, reference entity gross debt, a dummy taking value 1 if the reference entity is French, and $log(|Exp|)_{ijt}$, the log of the absolute total (CDS plus debt) credit risk exposure (when analyzing long and short speculating strategies), or the log of total debt exposure (when analyzing hedgers). Investor-quarter fixed effects control for any economy-wide change in demand or supply for CDS (for instance, regulatory changes), as well as investor-level shocks. We therefore measure the within-investor propensity to trade CDS depending on reference entity risk.

In these analyses, liquidity controls are particularly important. CDS relative liquidity may be higher for riskier reference entities for which debt issues are more fragmented, and debt trades smaller.[28] Should part of the relative liquidity between bonds and CDS be attributable to the features of bond supply (i.e., whether bonds are fragmented and trades small), one may confound demand for liquidity with demand for credit risk. We control for the liquidity of bonds and CDS as measured by the bond and CDS bid-ask spreads, and add a dummy if the reference entity is one of the top 1000 most traded CDS in that quarter. This allows to isolate pure demand for credit risk.

Estimation results are housed in Table 2.5. Column (1) studies the probability to use CDS for short credit risk investors, the ones having a negative total (CDS and debt) exposure to credit risk. Using CDS on these strategies significantly relates to CDS spreads for banks and dealers. The coefficient on investment funds is not significant, but there are too little bond short-selling positions in our sample of funds which implies that funds almost exclusively use CDS for short speculation, irrespective of risk levels (see Figure 2.11 in Appendix D). Quantitatively, the effect remains moderate. The probability of using CDS instead or on top of a short-selling position increases by 1.2pp (resp. 0.41pp) for banks (resp. dealers) for every percentage point increase in the CDS spread.

Column (2) instead discusses the case of hedgers. The demand for hedging increases with reference entity spread for all sectors, and more so for investment funds. As regards long credit risk only investors in column (3), higher spreads relate to a higher propensity to trade CDS for all sectors as well.

Dealers are sensitive to reference entity risk in all strategies, partly due to their own strategy, but also mirroring the demand of other sectors as their role is also to intermediate

[28]Oehmke and Zawadowski (2017) show that more CDS trading happens when the corresponding debt securities are more fragmented. Biswas et al. (2015) show that CDS are relatively more liquid for trades up to 500k$, while the opposite holds for larger trades.

transactions and adapt their inventories to client demand. As expected, we also find that both measures of higher CDS liquidity correlate with more CDS trading for all strategies.

Our results are broadly consistent with theory. Hedgers appear to increase hedging for riskier exposures consistent with Atkeson et al. (2015). Increasing short speculation by non-dealers on riskier reference entities is consistent with higher disagreement, lower margin requirements, and higher opacity associated to higher credit risk.

5.2. Robustness

Tables 2.12 in Appendix E provide robustness to the result that investors use CDS for risk-taking, by replicating estimations similar to those of Jiang et al. (2021). Table 2.12 simply estimates the mean investor-level difference in the spread of CDS sold versus the equivalent spread of bonds, for long speculation exposures. It indicates that all sectors tend to sell CDS of spreads higher than their average bond holding.

In Figures 2.11 and 2.12 in Appendix D, we examine the unconditional share of CDS in long and short credit risk exposures, by sector. It is immediately visible that the share of CDS increases with credit risk in all cases. The only exception is long speculators among investment funds: unconditionally, the share of CDS sold in total exposures decreases with credit rating. This suggests that while all investment funds tend to use CDS for risk-taking, those specialized in less risky assets will tend to do so more.

5.3. Rating arbitrage

CDS may also be a trading venue for rating arbitrage. As emphasized by the literature (Becker and Ivashina, 2015; Boermans and van der Kroft, 2020; Choi and Kronlund, 2018), some types of investors may have incentives to hold disproportionate amounts of bonds paying above-average spreads within their rating notch. This behavior can stem from rating-based capital requirements in the banking sector (see footnote 5), or from window-dressing incentives. Jiang et al. (2021) also identify these trading strategies across US mutual funds. The opportunities for rating arbitrage may be higher with CDS which are not in fixed supply.

We test whether our different strategies relate to rating arbitrage. To do so, we estimate an equation similar to Equation (2.6), substituting the spread by the z-score of each spread within its rating category. Z-score are calculated by rating notch in the distribution of reference entity-quarter observations. We round all ratings at the letter level using the scale of S&P. Results are presented in Table 2.13 in Appendix E.

Most investors do seem to pursue rating arbitrage in different manners. Investment fund long speculators display a higher propensity to trade CDS on high spread Z-score reference

entities, but also a higher propensity to hedge them. Since the coefficient on hedgers in smaller in magnitude, this rather points towards a rating arbitrage behavior. Bank short speculators trade more CDS on high Z-score reference entities, and hedge them less. Finally, dealers only seem to hedge less their high Z-score reference entities.

6. Conclusion

In this paper, we use quarterly granular data on both debt and CDS exposures to study how CDS reallocate credit risk across investors. CDS represent a limited share of aggregate credit risk exposures, but a large share of exposures to the reference entities on which CDS are traded. We propose a methodology to disentangle CDS positions into three strategies: speculators use CDS to amplify their original debt exposures or originate new ones; hedgers use them to reduce debt exposures after unexpected shocks or to maintain lending relationships; arbitrageurs make profit out of the CDS-bond basis, but represent an anecdotal share of strategies.

CDS trading affects credit risk allocation in three manners. First, the introduction of CDS increases the amount of outstanding credit risk exposures, by 10 to 15% on the subsample of large NFCs which reference CDS. CDS also impact credit risk concentration, with hedgers using CDS to shed off their most concentrated exposures, while speculators complement their existing debt exposures by selling CDS. Finally, CDS facilitate risk-taking for most sectors and trading strategies, thereby increasing the average riskiness of credit risk exposures.

Overall, the consequences of credit risk redistribution for financial stability appear ambiguous since hedging the most concentrated and riskiest exposures potentially offsets the other effects identified. Measuring the contribution of CDS to systemic risk through higher granular risk in a normative framework is left for future research.

	$P(CDS \neq 0)$		
	P(Short Speculator)	P(Hedger)	P(Long Speculator)
	(1)	(2)	(3)
Bank:Spread	0.44^{***}	0.07^{**}	0.17^{***}
	(0.09)	(0.03)	(0.05)
Dealer:Spread	0.15^{**}	0.06^{***}	0.11^{***}
	(0.07)	(0.02)	(0.03)
Fund:Spread	-2.66	0.18^{***}	0.20^{***}
	(3.45)	(0.03)	(0.02)
Log |Total|	1.09^{***}		0.51^{***}
	(0.05)		(0.03)
Log |Debt|		0.76^{***}	
		(0.03)	
FR Ref	-1.27	0.09	-0.43^{***}
	(1.12)	(0.10)	(0.09)
CDS bid-ask spread Ref	-3.29^{***}	-3.02^{***}	-4.85^{***}
	(0.57)	(0.44)	(0.47)
Bond bid-ask spread Ref	-0.92	-0.49	-1.53^{***}
	(0.88)	(0.44)	(0.27)
Top1000 CDS liquidity Ref	1.59^{***}	0.37^{***}	0.94^{***}
	(0.18)	(0.11)	(0.11)
Log gross debt Ref	-0.59^{***}	-0.06^{***}	-0.10^{***}
	(0.08)	(0.02)	(0.02)
Inv x Quarter FE	Y	Y	Y
IBP correction	Y	Y	Y
APE Bank	1.22	0.14	1.02
APE Dealer	0.41	0.13	0.67
APE Fund	-7.36	0.37	1.22
Num. obs.	4195	26077	73465

Notes: Estimation of Equation (2.6). Coefficients correspond to the mean expected increase in the log odds ratio of trading CDS, per unit increase in explanatory variables. Columns (1) and (3) include respectively only short (resp. long) credit risk strategies. Column (2) includes only strategies with long debt and weakly short CDS positions, and the dependent variable takes the value 1 if the position is identified as a hedging position using our methodology. Insurers are excluded from the analysis. CDS spreads are right-winsorized at 1%, bid-ask spreads and the CDS-bond basis are winsorized at 0.5% on both sides. Spreads are expressed in percentage points. Coefficients are corrected from the incidental parameter bias using the methodology developed by Fernández-Val and Weidner (2016). *APE* designates the average marginal effect (in percentage points) of the spread (in percentage points) over the sample. Standard errors are clustered at the investor-quarter and reference entity-quarter level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 2.5: Probability to trade CDS depending on reference entity spread

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A. Data cleaning

A.1. Cleaning CDS positions from DTCC reports

EMIR Regulation (648/2012) compels EU institutions to report their derivative transactions to trade repositories, which in turn transfer the required data to regulators. We use quarter-end credit derivatives reports to *DTCC* from 2016$Q1$ to 2021$Q4$. Abad et al. (2016) find that *DTCC* accounts for the bulk of transactions that fall under EMIR scope. Since all major dealers report their trades to *DTCC*, data from this trade repository is representative of the European market for credit derivatives. We apply a series of treatments to clean the data. First, we remove transactions for which the column CCP is filled but no counterparty is a CCP. These are old alpha transactions that are novated with a CCP and that the counterparties forgot to terminate. Second, we enrich the data with FX rates to convert notionals in euros and we match the contract ISIN with Anna-DSB to retrieve the ISIN (or index name) of the reference entity. Third, transactions are de-duplicated and turned into one-liner observations. We remove observations if the two reporting counterparties disagree on key fields: reference entity, contract type, notional, currency, contracts resulting from compression, execution date, maturity date, intragroup dummy. Fourth, we remove transactions with missing execution date, maturity date, reference entity, or valuation. We also drop intragroup transactions, position components, and transactions with notionals under (and above) €1000 (€10bn). Finally, we restrict our dataset to credit default swaps contracts and remove more exotic contracts such as spread bets or swaptions.

A.2. Reference entity rating

To construct a rating for each reference entity, we rely on four different sources: *CSDB*, Thomson Reuters, Banque de France internal ratings, and *Solvency II* (SII) reported ratings by insurer companies. We prioritize the issuer rating over the ISIN rating in *CSDB*. If there is no issuer rating, then we average by reference entity the corresponding ratings for long-term unsecured ISIN. We fill missing ratings with those downloaded from Thomson Reuters, Banque de France, and SII, with this order of prioritisation. When using SII data, we only keep reference ratings when they are reported at least two insurers and when no disagreement exists between these insurers.

A.3. Cleaning reference entity CDS spreads

CDS spreads and CDS-bond basis are obtained from *Refinitiv* and completed by *Markit* data (for around 400 references). We extract all non-financial corporate CDS spreads (and

CDS-bond basis) from the main countries of residence of the reference entities in our database (Belgium, Caiman Islands, Canada, France, Germany, Hong-Kong, Italy, Japan, Luxembourg, Netherlands, South Korea, Spain, Sweden, the United Kingdom, and the United States), as well as those composing the main CDS indices.

CDS quotations are identified at the RIC level in *Refinitiv* which also provides the corresponding LEI. We use the LEI to match CDS spreads to the relevant reference entity. When there are multiple CDS quoted for a single reference entity, we select them based on the following pecking order of criteria: (1) the quotation norm, using in priority the most standard norm used on the European market (modified-modified restructuring > modified restructuring > cum restructuring > ex restructuring); (2) the currency, privileging the euro over the USD over the GBP; (3) the number of observations available since 2011. We end up with a single CDS spread and CDS-bond basis time series for each reference entity in our sample.

B. A methodology to disentangle strategies

Our methodology aims at disentangling speculators, hedgers, and arbitrageurs by exploiting the sign, nature, and timing of matched debt and CDS positions at the investor-reference entity-quarter level. In our approach, a trading strategy for CDS_{ijt} is the reason why an investor i holds a CDS on reference entity j at quarter t. By convention, a negative exposure is short on credit risk, and a positive exposure is long on credit risk. For ease of notation, we denote a holding $(CDS_{ijt}, Debt_{ijt})$ with a tuple of signs (e.g., $(-,+)_t$), where signs correspond to our convention, and 0 corresponds to the absence of positions. An identified strategy is assumed to prevail until either the CDS or the debt position is unwound or changes sign. We proceed with the following steps, which are summarized in Figure 2.6.

Step 1: We examine whether debt and CDS weakly amplify ($CDS_{ijt} \times Debt_{ijt} \geq 0$) or strictly offset ($CDS_{ijt} \times Debt_{ijt} < 0$) each other. When there is no CDS exposure, the position is *standard*. When CDS and debt exposures amplify each other, investors are considered as *speculators*. Speculators may be *naked* if there is no underlying debt.

Step 2: Among *offsetters*, we single out positions whose hedging ratio is such that $\frac{CDS_{ijt}}{Debt_{ijt}} \leq -1.2$. These investors are *naked speculators* since the bulk of the CDS creates a negative net position rather than offsets existing debt.

Step 3: We use the timing of entry in positions to disentangle the remaining offsetters for which we observe entry.

Case 1: If the debt position leads the offsetting CDS position (moving from $(+,+)_{t-1}$ or $(0,+)_{t-1}$ to $(-,+)_t$, or symmetrically when hedging a short debt position), then the investor is a *hedger*. This corresponds to the case when hedgers adjust their credit risk position in response to a shock.

Case 2: If both short CDS and debt positions are acquired in a single period, moving from $(+,-)_{t-1}$, $(+,0)_{t-1}$, $(0,-)_{t-1}$ or $(0,0)_{t-1}$ to $(-,+)_t$, and part of the debt is a loan, then the investor is a *hedger*. This corresponds to the case when hedgers seek to maintain a lending relationship by purchasing a CDS. Therefore, the sequence does not apply to $(+,-)_t$ positions.

Case 3: If both short CDS and debt positions are acquired in a single period, moving from $(+,-)_{t-1}$, $(+,0)_{t-1}$, $(0,-)_{t-1}$ or $(0,0)_{t-1}$ to $(-,+)_t$, and all debt instruments are debt securities, then the investor is an *arbitrageur* since maintaining a lending relationship can only occur when extending a loan.

Case 4: If both long CDS and debt positions are acquired in a single period, moving

from $(-,+)_{t-1}$, $(-,0)_{t-1}$, $(0,+)_{t-1}$ or $(0,0)_{t-1}$ to $(+,-)_t$, then the investor is an *arbitrageur*.

			Position at t		
			(-,+ incl loans) and hedging ratio>-1.2	(-,+ bonds only) and hedging ratio > -1.2	(+,-) and hedging ratio > -1.2
Position at t-1	No position	(0,0)	Hedger	Arbitrageur	Arbitrageur
	Short naked speculator	(-,0)	Other	Other	Arbitrageur
	Long naked speculator	(+,0)	Hedger	Arbitrageur	Other
	Standard long debt	(0,+)	Hedger	Hedger	Arbitrageur
	Short offsetter	(-,+)	Non identified	Non identified	Arbitrageur
	Long speculator	(+,+)	Hedger	Hedger	Other
	Standard short debt	(0,-)	Hedger	Arbitrageur	Hedger
	Short speculator	(-,-)	Other	Other	Hedger
	Long offsetter	(+,-)	Hedger	Arbitrageur	Non identified

Fig. 2.6. Summary of step 3 possibilities to identify offsetting positions

Step 4: For offsetters for which we observe exit but not entry, we start by calculating the hedging ratio in the first period of observation (2016Q1). This additional criterion is helpful since investors hedging bonds in response to shocks may exit simultaneously, and therefore be indistinct from arbitrageurs. We use Bayes rule to calculate the probability that the hedging ratio is that of a hedger or an arbitrageur, assuming both strategies have the same unconditional probability,[29] and after estimating the pooled distribution of hedging ratios (HR) for each strategy using a gaussian kernel:

$$\mathbb{P}(Arb|HR) > \mathbb{P}(Hed|HR) \Leftrightarrow \mathbb{P}(HR|Arb) > \mathbb{P}(HR|Hed).$$

<u>Case 1:</u> If the CDS position is unwound before the debt position, moving from $(-,+)_{t-1}$ to $(+,-)_{t-1}$, $(+,0)_{t-1}$, $(0,-)_{t-1}$ or $(0,0)_{t-1}$, or symmetrically for selling CDS, then the investor is a *hedger*.

<u>Case 2:</u> If short CDS and debt positions are unwound in a single period, moving from $(-,+)_{t-1}$ to $(+,-)_{t-1}$, $(+,0)_{t-1}$, $(0,-)_{t-1}$ or $(0,0)_{t-1}$, and part of the debt is a loan, then the investor is a *hedger*.

<u>Case 3:</u> If short CDS and bond only positions are unwound in a single period, moving from $(-,+)_{t-1}$ to $(+,-)_{t-1}$, $(+,0)_{t-1}$, $(0,-)_{t-1}$ or $(0,0)_{t-1}$, then the investor is of the most likely strategy given the hedging ratio as of 2016Q1.

<u>Case 4:</u> If long CDS and debt positions are unwound in a single period, moving from $(+,-)_{t-1}$ to $(-,+)_{t-1}$, $(-,0)_{t-1}$, $(0,+)_{t-1}$ or $(0,0)_{t-1}$, then the investor is an arbitrageur.

Step 5: All other strategies, for which we observe neither entry nor exit, or for which

[29] If we use observed unconditional probabilities, hedgers are more likely than arbitrageurs for any hedging ratio.

entry and exit do not follow one of the described patterns, are considered as *others*.

C. Bootstrapping procedure

We follow Cameron et al. (2008) and develop a cluster (also known as block) bootstrap procedure. We compute confidence intervals using the bootstrap-t procedure from Efron (1981). This method relies on an asymptotically pivotal statistics for confidence intervals which performs better asymptotically than boostrap-se procedures. The algorithm proceeds in steps:

1. Estimate the two stages models (2.3) and (2.4) on the original sample and compute the Wald test statistics:

   $$w = \hat{\beta}/\hat{\sigma}_{\hat{\beta}}$$

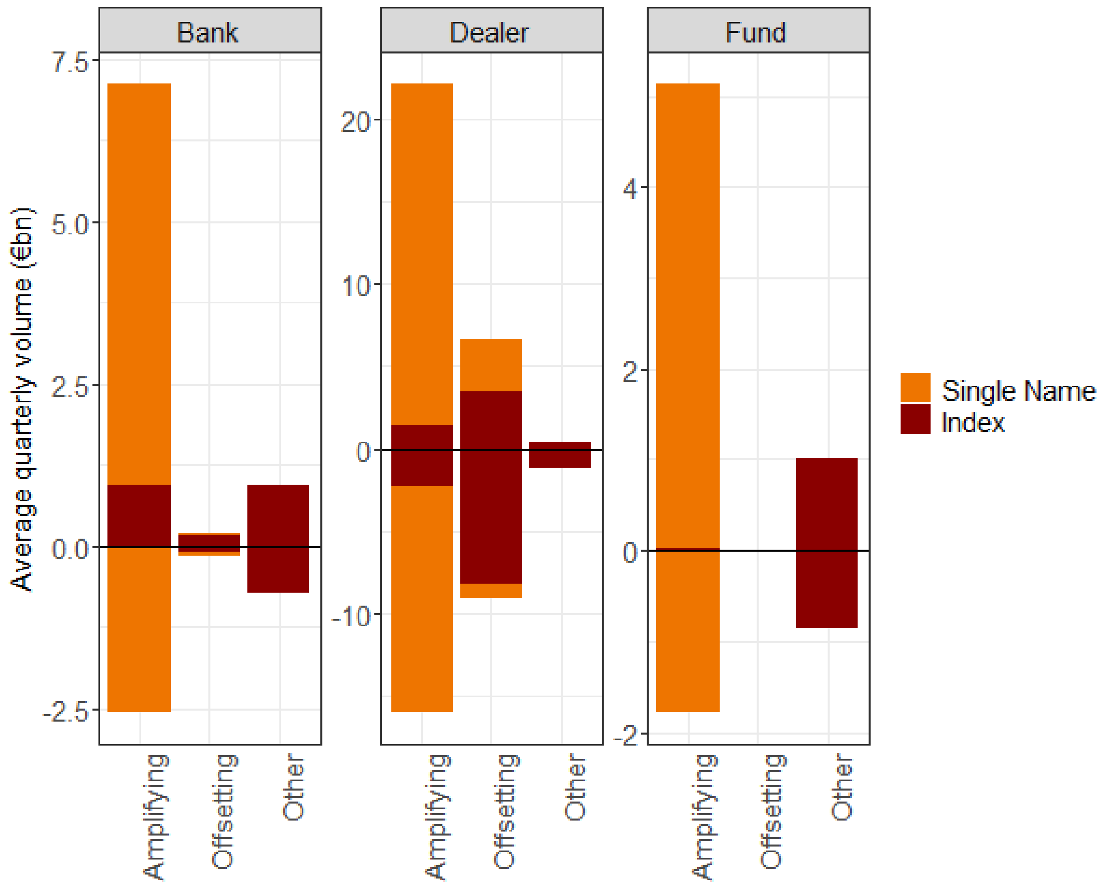
   The Wald statistics tests the null hypothesis for the coefficient $\hat{\beta}$. $\hat{\sigma}_{\hat{\beta}}$ is the cluster-robust variance estimator at the investor-quarter and reference entity-quarter levels.
2. Repeat $B = 999$ iterations. The b-th iteration:
   (a) Draws G clusters with replacement from the original sample of reference entity-quarter clusters to form the bootstrapped b-sample. G denotes the number of unique reference entity-quarter.
   (b) Estimates the two stages model (2.3) and (2.4) on the b-sample and compute the Wald test statistics:

   $$w_b^* = \frac{\hat{\beta}_b^* - \hat{\beta}}{\hat{\sigma}_{\hat{\beta}_b^*}}$$

   with $\hat{\sigma}_{\hat{\beta}_b^*}$ the b estimation clustered standard error. The Wald test statistics w_b^* tests the null hypothesis that the coefficient from the b-sample is equal to the coefficient from the original sample.
3. Retrieve the distribution of Wald test statistics w^* and its quantiles at the α level, $w^*_{[\alpha/2]}$ and $w^*_{[1-\alpha/2]}$.
4. Reject the null hypothesis if $w < w^*_{[\alpha/2]}$ or $w > w^*_{[1-\alpha/2]}$. This is equivalent to form the following confidence interval around $\hat{\beta}$:

$$[\hat{\beta} - w^*_{[1-\alpha/2]}\hat{\sigma}_{\hat{\beta}}; \hat{\beta} - w^*_{[\alpha/2]}\hat{\sigma}_{\hat{\beta}}] \tag{2.7}$$

D. Additional figures



Notes: The figure presents the mean amount of CDS and index positions by investor sector in the pooled strictly post-2017Q4 sample for NFC reference entities. It splits single name and index positions in three cases: *amplifying* refers to CDS and index exposures with the same sign, *offsetting* refers to CDS and index exposures having opposite signs, and *other* positions include a null single name or index position.

Fig. 2.7. Respective signs of single name and index positions by investor sector

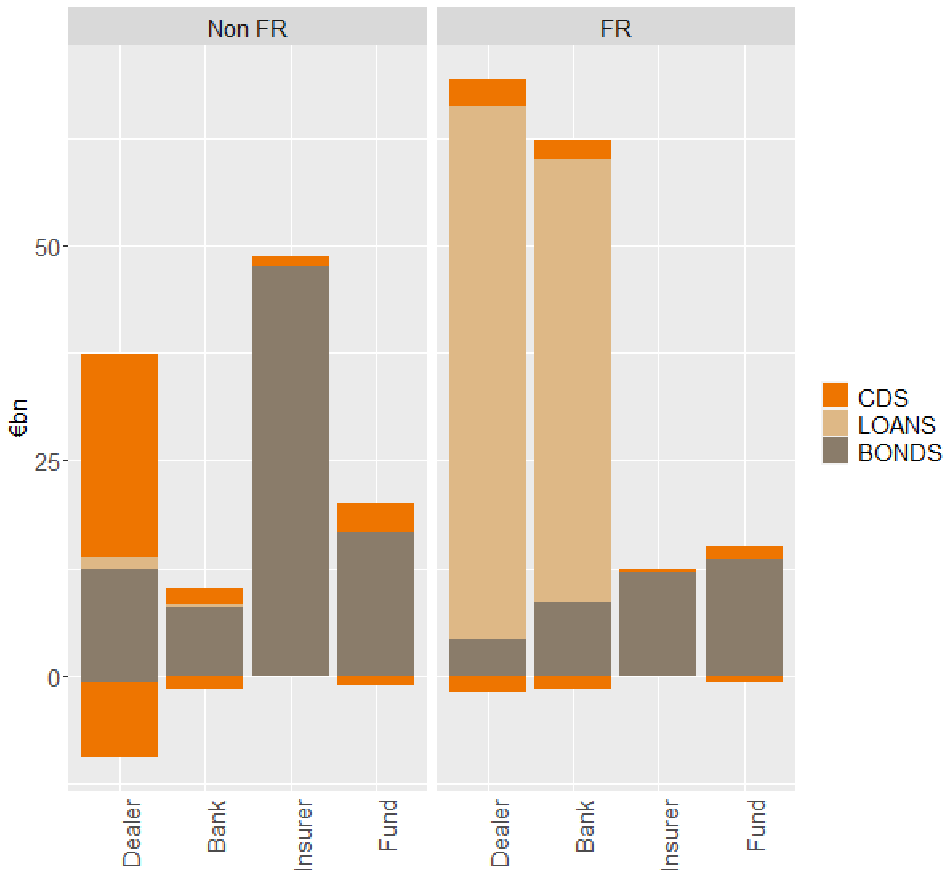


Fig. 2.8. Debt and CDS exposures to NFC by investment sector and residence of reference entity as of 2019Q4

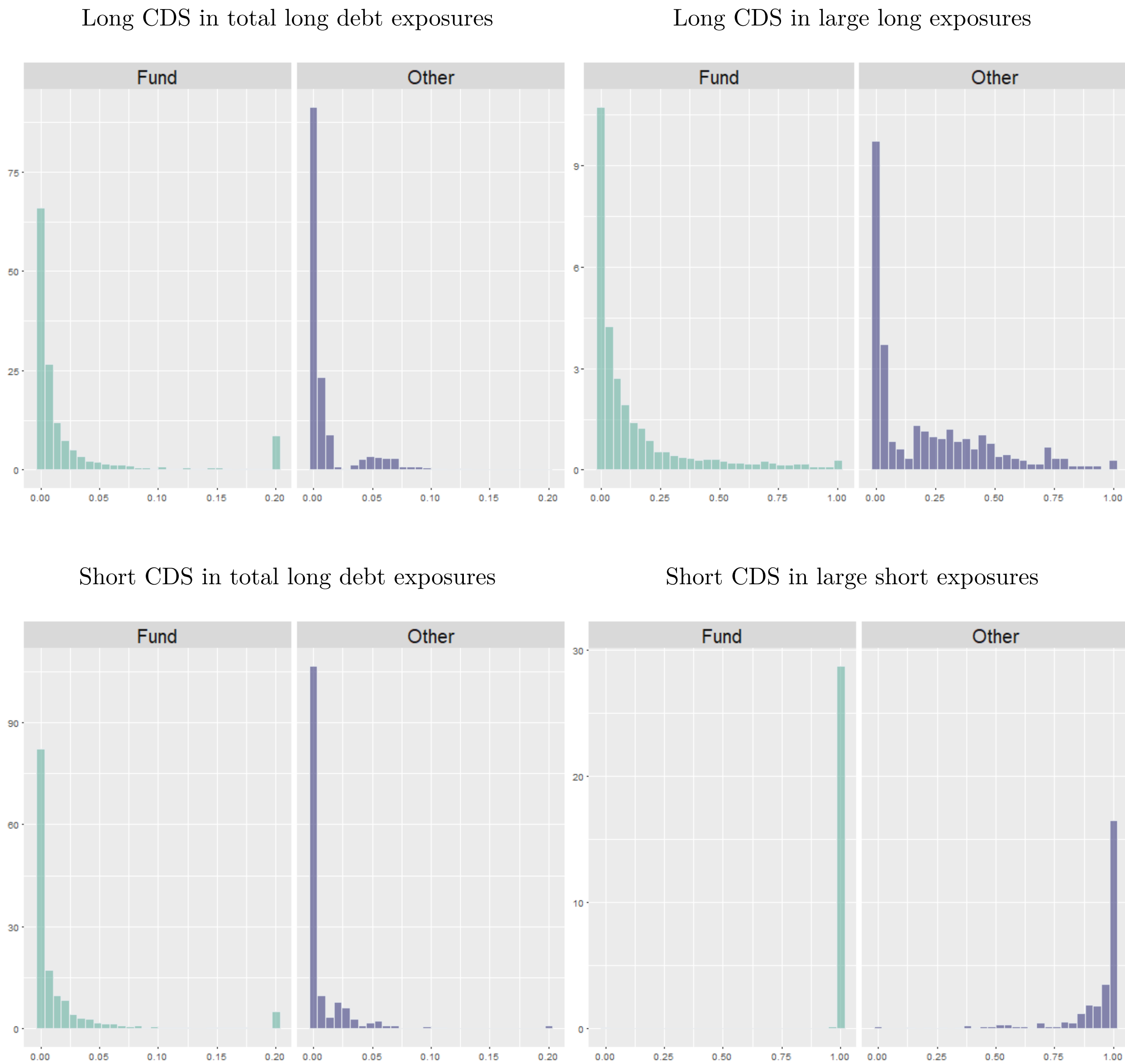


Fig. 2.9. Pooled distribution of the share of CDS positions per investor

Notes: Charts on the left-hand side represent CDS shares of total observed long debt exposures. These distributions are right-censored at 20%. Charts on the right-hand side represent CDS shares of (long or short) total (CDS and debt) exposures to firms referencing CDS at least once in our sample ("large" firms). Exposures with no CDS holdings are excluded for readability.

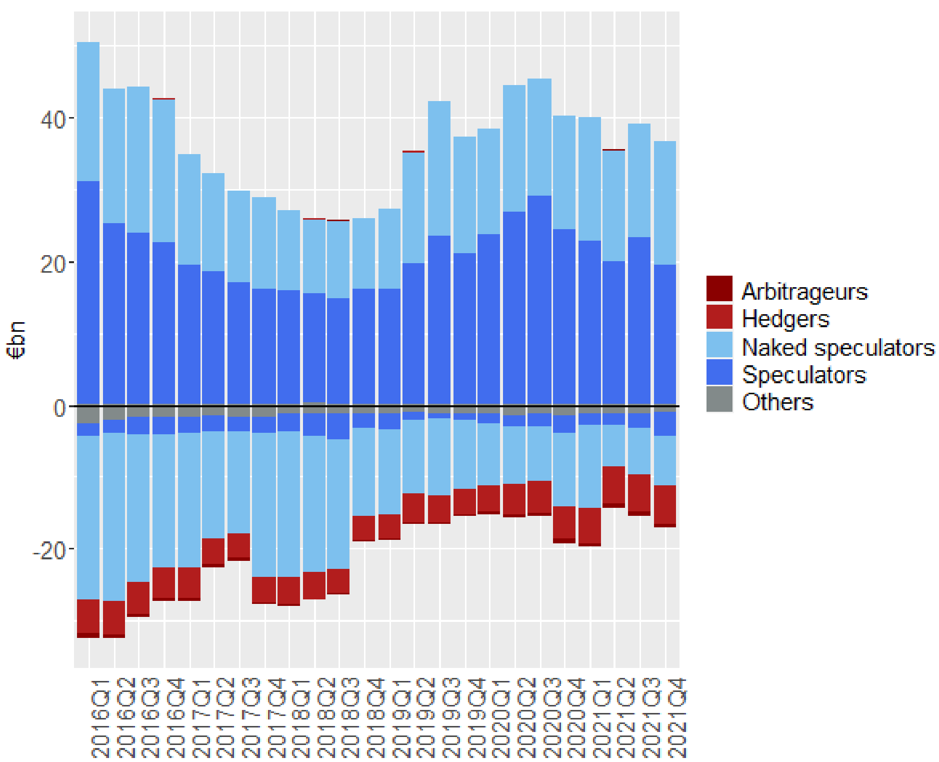
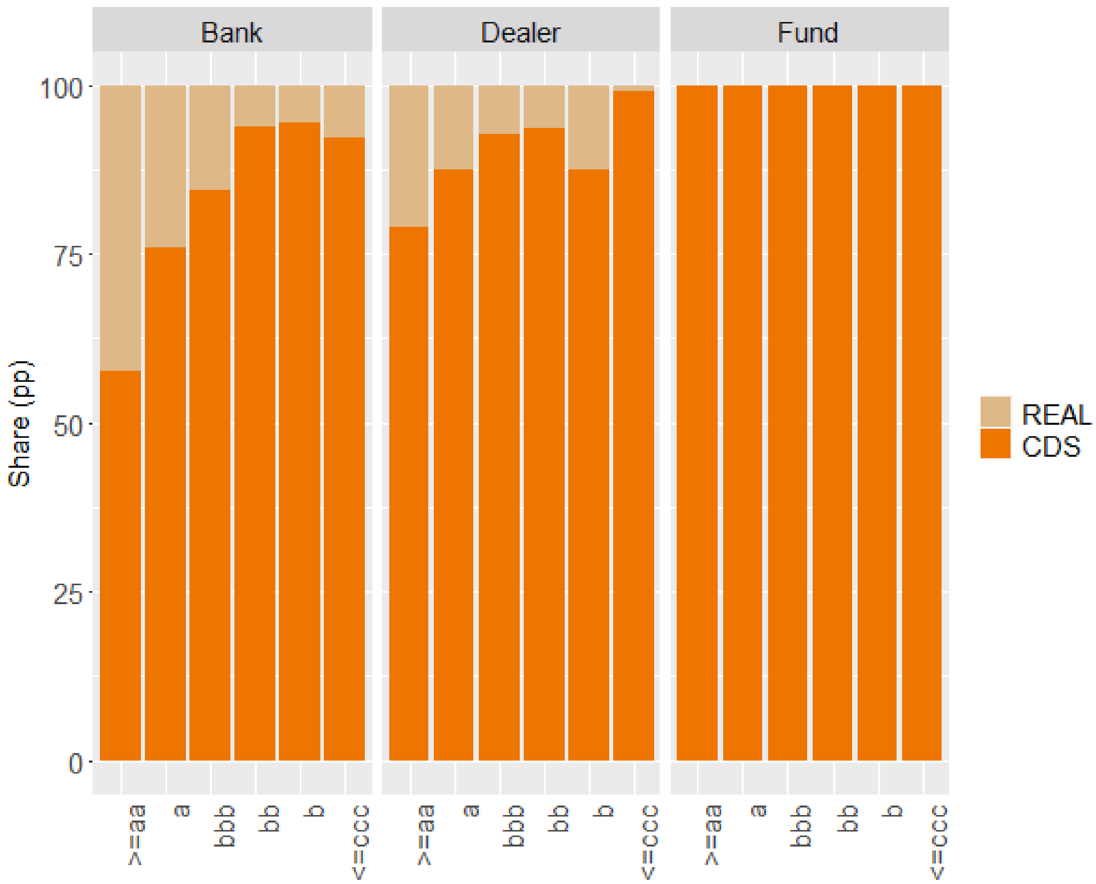
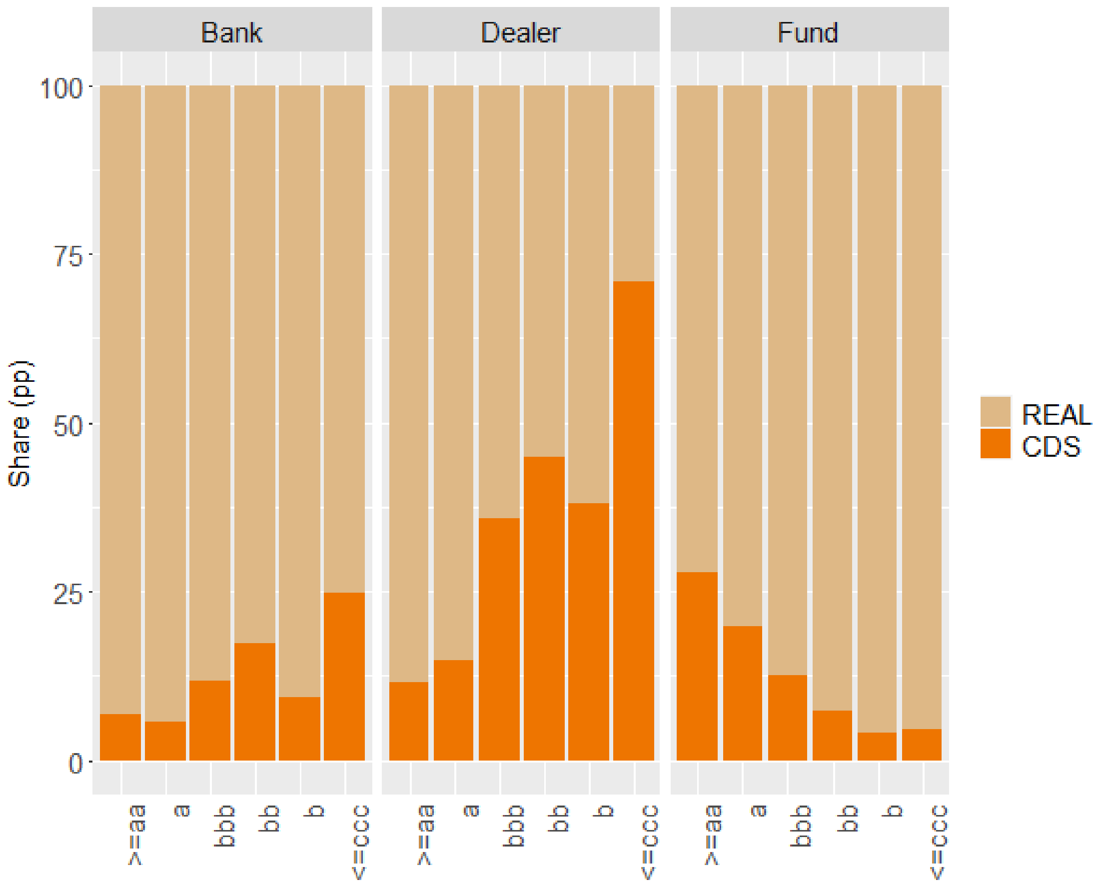


Fig. 2.10. CDS net exposures by strategy over time



Notes: Reference entities in default are excluded.

Fig. 2.11. Share of CDS in short speculation exposures by sector and rating



Notes: Reference entities in default are excluded.

Fig. 2.12. Share of CDS in long speculation exposures by sector and rating

E. Additional tables

Rating	#Ref-Date	CDS sell	CDS buy	Debt long	Debt short	Spread	Basis	CDS bid-ask	Bond bid-ask
>=aa	50	1.69	-0.59	17.08	-0.05	31.09	-6.80	23.99	0.27
a	219	7.58	-3.75	88.61	-0.31	45.45	-6.30	18.16	0.36
bbb	498	17.14	-8.18	104.11	-0.44	72.93	-8.40	12.09	0.38
bb	305	5.30	-2.87	16.22	-0.11	186.45	-43.50	11.48	0.95
b	232	3.02	-1.23	11.50	-0.08	382.87	-11.85	7.88	1.29
<=ccc	96	0.91	-0.47	0.93	-0.00	729.53	-9.81	11.98	2.71
Default	31	0.04	-0.01	0.04	0.00	2883.69		4.13	13.06
Missing	573	0.99	-0.33	13.00	-0.01	101.47	-25.80	17.05	0.57

Notes: Statistics over all reference-dates with at least one non-null exposure in our database. *#Ref-Date* is the number of reference-date unique observations. *CDS sell* and *CDS buy* are the pooled strictly post-2018Q2 average net CDS positions by period. Spreads, basis spreads, and bid-ask spreads are all median. *CDS bid-ask* is the difference between the bid and the ask spread divided by the mean spread, expressed in basis points. *Bond bid-ask* is the difference between the bid and the ask price divided by the mean price, expressed in percentage points. Spreads are expressed in basis points.

Table 2.6: Descriptive statistics of references

	Basis	
	Baseline	Liquidity controls
	(1)	(2)
Spread	3.724***	0.936
	(0.714)	(0.807)
Short arbitrage	-22.809***	-23.620***
	(5.334)	(5.257)
Standard long debt	-9.912***	-8.219***
	(1.543)	(1.522)
Standard short debt	-0.918	7.163**
	(3.257)	(3.356)
Short speculation	-10.899***	-10.694***
	(1.854)	(1.863)
Long speculation	-2.865	-4.087**
	(1.879)	(1.883)
Long arbitrage	-22.589	-11.074
	(17.666)	(14.522)
Long offsetting	0.067	0.461
	(3.283)	(3.454)
CDS bid-ask Ref		-75.407***
		(3.707)
Bond bid-ask Ref		6.592***
		(2.182)
Top1000 CDS liquidity Ref		-0.079
		(0.856)
Inv x Quarter FE	Y	Y
Adjusted R^2	0.145	0.173
Num. Obs.	94538	87902

Notes: Strategy wrt short offsetters other than short arbitrageurs. CDS spreads are right-winsorized at 1%, bid-ask spreads and the CDS-bond basis are winsorized at 0.5% on both sides. Standard errors are clustered at the investor-quarter level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 2.7: CDS bond basis by strategy

Strategy	#Positions	Debt	CDS	HedgRatio	ResMat Debt	ResMat CDS	ShareCCP	Persistence	Turnover Debt	Turnover CDS
Standard	20755.00	16.33	0.00	0.00	9.26	1.87	0.05	4.95	0.26	0.00
Others	202.00	0.48	0.12	0.71	6.35	2.57	0.08	6.39	0.00	0.00
Speculators	2069.00	71.93	26.46	1.64	7.30	3.04	0.20	3.13	1.20	0.59
Naked speculators	3225.00	1.15	18.26	7.78	8.36	2.81	0.17	3.17	0.10	0.45
Hedgers	471.00	180.16	20.27	0.22	6.11	2.80	0.12	3.10	0.22	0.75
Arbitrageurs	92.00	13.28	11.22	1.00	3.80	2.66	0.03	3.55	0.19	0.19

Notes: Statistics are pooled by strategy, irrespective of the sign of the CDS position. *#Position* corresponds to the average number of non-null positions of each strategy by quarter since 2018Q3. *Debt* and *CDS* correspond to the mean face and notional value of any single position, in €mn. *HedgRatio* is the median absolute hedging ratio $\frac{|CDS_{ijt}|}{|Debt_{ijt}|}$. *ResMatDebt* and *ResMatCDS* are mean residual maturity of debt and CDS in years. *ShareCCP* is the mean notional-weighted share of positions by investor-reference-quarter cleared through a CCP. *Persistence* is calculated as the mean duration of each strategy in our sample in quarters. *TurnDebt* and *TurnCDS* are debt and CDS turnovers within a strategy (intensive margin), calculated as absolute growth rates, trimmed at the 1% level. *Naked speculators* include *offsetters* with hedging ratios below -2, hence the non-null debt exposures for this strategy. The high persistence of *Others* is attributable to our strategy identification method which requires the observation of entry or exit to allocate positions to specific strategies.

Table 2.8: Descriptive statistics by strategy

Investor sector	Strategy	Mean	Median	5% quantile	95% quantile	Standard deviation
Bank	Hedger	0.20	0.11	0.01	0.73	0.21
Bank	Speculator	0.11	0.03	0.00	0.63	0.18
Bank	Standard	0.08	0.02	0.00	0.38	0.14
Dealer	Hedger	0.15	0.07	0.00	0.46	0.16
Dealer	Speculator	0.04	0.00	0.00	0.27	0.10
Dealer	Standard	0.03	0.00	0.00	0.17	0.08
Fund	Hedger	1.04	0.88	0.08	2.62	0.77
Fund	Speculator	0.72	0.50	0.04	2.20	0.66
Fund	Standard	0.68	0.50	0.04	2.05	0.61

Notes: Exposures are restricted to strictly positive debt exposures. Debt exposure shares are calculated by dividing debt exposures by total debt holdings. They are right-winsorized at the 2.5% level, and expressed in percentage points. The table presents the moments of their distribution by investor sector and strategy.

Table 2.9: Debt exposure shares by sector and strategy

	Debt share		
	Bank	Dealer	Fund
	(1)	(2)	(3)
Share gross debt	0.53^{***}	0.41^{***}	0.19^{***}
	(0.04)	(0.03)	(0.01)
Log Gross debt Ref	0.00^{***}	0.00^{***}	-0.00
	(0.00)	(0.00)	(0.00)
Spread Ref	-0.01^{***}	-0.00^{***}	-0.00
	(0.00)	(0.00)	(0.00)
CDS bid-ask spread Ref	-0.07^{***}	-0.05^{***}	-0.16^{***}
	(0.02)	(0.01)	(0.05)
FR Ref	0.33^{***}	0.24^{***}	0.07^{***}
	(0.01)	(0.01)	(0.01)
CQS Ref	-0.01^{***}	-0.01^{***}	-0.00
	(0.00)	(0.00)	(0.01)
Inv x Quarter FE	Y	Y	Y
Kleibergen-Paap Wald test	181.07	151.65	277.83
Adjusted R^2	0.50	0.65	0.39
Num. obs.	11493	13077	108429

Notes: Estimation of Equation (2.3). The sample includes all strictly positive debt positions. The dependent variable *Debt share* and the explanatory variable *Gross debt share* are both right-winsorized at 2.5%. CDS spreads are right-winsorized at 1% and CDS bid-ask spreads are winsorized at 0.5% on both sides. Spreads are expressed in percentage points. *CQS Ref* is the Credit Quality Step of the reference entity expressed in units, with higher units referring to higher risk of default. Standard errors are clustered at the investor-quarter and reference entity-quarter level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 2.10: Debt exposure concentration and CDS trading, first-stage regression

	P(Long Naked Speculator)		
	Bank (1)	Dealer (2)	Fund (3)
Debt share	1.25^{*}	9.82^{*}	-0.01
	$[0.63; 1.48]$	$[6.12; 13.12]$	$[-0.04; 0.01]$
Log gross debt Ref	-0.21^{*}	-0.33^{*}	-0.08^{*}
	$[-0.27; -0.13]$	$[-0.48; -0.20]$	$[-0.10; -0.04]$
Spread Ref	0.28^{*}	0.45^{*}	0.17^{*}
	$[0.21; 0.36]$	$[0.07; 0.90]$	$[0.12; 0.20]$
CDS bid-ask spread Ref	-4.42^{*}	-4.23^{*}	-5.13^{*}
	$[-5.73; -3.38]$	$[-6.31; -2.43]$	$[-6.11; -4.19]$
FR Ref	-13.38^{*}	-47.48^{*}	-0.00
	$[-15.67; -10.25]$	$[-592167.73; -35.49]$	$[-0.12; 0.12]$
CQS Ref	0.48^{*}	1.24^{*}	-0.00
	$[0.23; 0.60]$	$[0.94; 1.63]$	$[-0.07; 0.08]$
First stage residuals	-2.18^{*}	-10.31^{*}	-0.40^{*}
	$[-2.60; -1.58]$	$[-14.08; -6.21]$	$[-0.44; -0.37]$
Kleibergen-Paap Wald test	62.422	32.596	4532.058
First-stage coefficient	0.339	0.046	0.607
Inv x Quarter FE	Y	Y	Y
IBP correction	Y	Y	Y
APE	0.12	0.97	-0.00
Num. obs.	6574	5226	38436

Notes: Estimation of Equation (2.4). The sample includes all weakly positive debt positions. *Debt share* is right-winsorized at 2.5%. CDS spreads are right-winsorized at 1% and CDS bid-ask spreads are winsorized at 0.5% on both sides. Spreads are expressed in percentage points. *CQS Ref* is the Credit Quality Step of the reference entity expressed in units, with higher units referring to higher risk of default. Coefficients are corrected from the incidental parameter bias using the methodology developed by Fernández-Val and Weidner (2016). *APE* designates the average marginal effect (in points) of the debt share (in percentage points) over the sample. Standard errors are clustered at the investor-quarter and reference entity-quarter level. We present bootstrap confidence intervals at the 5% level, superscripts * indicate that the null is rejected at this threshold.

Table 2.11: Probability of long naked speculator and debt exposure concentration at the country-rating level

	$\Delta Spread$
	(1)
Bank	0.59^{***}
	(0.08)
Dealer	0.59^{***}
	(0.06)
Fund	0.23^{***}
	(0.05)
Adjusted R^2	0.02
Num. obs.	1215

Notes: The dependent variable is the notional-weighted spread of CDS sold minus bond owned, aggregated at the investor x quarter level. CDS spreads are right-winsorized at 1%. We restrict our analysis to investor-quarters with at least 5 CDS sell and 5 long debt positions. Reference entities in default are removed. Standard errors are clustered at the quarter level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 2.12: Difference between the average spread of CDS sold and the average spread of bonds owned by sector

	$P(CDS \neq 0)$		
	P(Short Speculator)	P(Hedger)	P(Long speculator)
	(1)	(2)	(3)
Bank:Spread Z-score	1.32^{***}	-0.24^{***}	0.09
	(0.30)	(0.08)	(0.06)
Dealer:Spread Z-score	0.02	-0.11^{**}	0.04
	(0.09)	(0.05)	(0.07)
Fund:Spread Z-score	4.67	0.11^{**}	0.20^{***}
	(4.27)	(0.05)	(0.03)
Log |Total|	1.08^{***}		0.50^{***}
	(0.06)		(0.03)
Log |Debt|		0.76^{***}	
		(0.03)	
FR Ref	-0.53	0.04	-0.39^{***}
	(1.07)	(0.10)	(0.09)
CDS bid-ask spread Ref	-3.63^{***}	-4.04^{***}	-5.41^{***}
	(0.66)	(0.53)	(0.53)
Bond bid-ask spread Ref	0.29	-0.44	-1.13^{***}
	(1.07)	(0.41)	(0.26)
Top1000 CDS liquidity Ref	1.54^{***}	0.21^{*}	0.87^{***}
	(0.18)	(0.11)	(0.11)
Log gross debt Ref	-0.62^{***}	-0.08^{***}	-0.13^{***}
	(0.08)	(0.02)	(0.02)
Inv x Quarter FE	Y	Y	Y
IBP correction	Y	Y	Y
APE Bank	3.77	-0.47	0.52
APE Dealer	0.05	-0.21	0.24
APE Fund	13.32	0.21	1.18
Num. obs.	3846	25294	71425

Notes: Estimation of Equation (2.6) replacing spreads by spread z-scores by rating notch. Z-scores are expressed in standard deviations. Coefficients correspond to the mean expected increase in the log odds ratio of trading CDS, per unit increase in explanatory variables. Columns (1) and (3) include respectively only short (resp. long) credit risk strategies. Column (2) includes only strategies with long debt and weakly short CDS positions, and the dependent variable takes the value 1 if the position is identified as a hedging position using our methodology. Insurers and reference entities in default are excluded from the analysis. CDS spreads are right-winsorized at 1%, bid-ask spreads and the CDS-bond basis are winsorized at 0.5% on both sides. Coefficients are corrected from the incidental parameter bias using the methodology developed by Fernández-Val and Weidner (2016). *APE* designates the average marginal effect (in percentage points) of the spread (in percentage points) over the sample. Standard errors are clustered at the investor-quarter and reference entity-quarter level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 2.13: Probability to trade CDS depending on spread Z-score by rating

Chapter 3

Habitat Sweet Habitat: the Heterogeneous Effects of Eurosystem Asset Purchase Programs

This chapter is based on a paper co-authored with Moaz Elsayed, Julien Idier and Thibaut Piquard (Banque de France).

Abstract

The impact of central bank asset purchase programs depends on the investment habitat of investors owning the assets purchased. Using granular data on Eurosystem purchases over 2014-2020, and on detailed securities holdings by financial institutions, we show that banks were the largest euro area counterparts to purchases of sovereign securities and covered bonds, while investment funds accommodated the bulk of corporate securities purchases. We also show that investors' rebalancing patterns depend on their habitat. Purchasing securities from banks will spur bank lending, while investment funds may increase their demand for riskier securities if they have the required mandate.

1. Introduction

The growing variety of asset purchase programs and the increasing flexibility that central banks have in implementing them,[1] suggest that all asset purchases are not equivalent. In particular, the portfolio rebalancing channel may operate differently depending on who initially owns the securities targeted and eventually purchased. Intuitively, purchasing securities owned by banks may support bank lending, while purchasing securities owned by investment funds may instead increase their demand for non-purchased and potentially riskier

[1]For example, the Eurosystem decided to allow flexible reinvesment of its PEPP portfolio reflects a willingness to support prices in specific segments of the market. See: `https://www.ecb.europa.eu/press/pr/date/2021/html/ecb.mp211216~1b6d3a1fd8.en.html`.

securities.

One of the most widely used theoretical framework to understand portfolio rebalancing is preferred habitat (PH) theory, pioneered by Tobin (1965). As Haruhiko Kuroda, former Governor of the Bank of Japan, put it:

> Whether central banks' large-scale asset purchases succeed in reducing term premiums hinges upon whether the preferred habitat hypothesis holds.

In that framework, central bank asset purchases operate by reducing the existing and expected amount of duration, liquidity and credit risk in the economy, thereby reducing the market price of risk (Vayanos and Vila, 2021; Altavilla et al., 2021). Accordingly, the type of assets purchased matters to the extent that each security bears a different amount of risk.

PH theory predicts that these heterogeneous effects may also depend on who initially owns the securities purchased. In the framework, demand for assets is segmented. *Arbitrageurs* have mean-variance preferences and ensure a no-arbitrage condition prevails across securities. Conversely, *preferred habitat* investors have price-sensitive demand over specific asset classes. This gives rise to two additional channels. First, asset purchases have local price effects. Reducing the supply of assets from PH investors' habitat increases the price of those assets above what would be predicted by the no-arbitrage condition of arbitrageurs only. For example, investment funds with a mandate for investing in euro area (EA) government debt securities may be reluctant to sell those by lack of alternative investment opportunities. Second, the segmentation of investors opens up the possibility of rebalancing across sectors. At constant asset supply, yield curve changes may affect relative asset demand. In the presence of balance sheet constraints, valuation gains may also disproportionately affect certain sectors and increase their demand for assets. But perhaps more importantly, changing the composition of asset supply by substituting debt securities with central bank reserves could trigger rebalancing as asset sellers recompose their optimal portfolio. As stated upon the announcement of quantitative easing by the European Central Bank (ECB):[2]

> The ECB will buy bonds issued by euro area central governments, agencies and European institutions in the secondary market against central bank money, which the institutions that sold the securities can use to buy other assets and extend credit to the real economy.

This type of rebalancing is further enhanced when the supply of assets increases - either mechanically when the central bank purchases securities from non-reserve holding institutions (Christensen and Krogstrup, 2016), or indirectly as a result of increased issuance (see

[2]See: `https://www.ecb.europa.eu/press/pr/date/2015/html/pr150122_1.en.html`.

for instance Abidi and Miquel-Flores (2018) or Todorov (2020) who show how the Corporate Sector Purchase Program (CSPP) stimulated corporate bond issuance). We dub it the ”liquidity-driven portfolio rebalancing channel”, and it will be the focus of this paper.

In this paper, we show that portfolio rebalancing differs depending on who owns the securities purchased. To address this question, one would ideally examine how two investors with different investment habitats rebalance upon selling the same security to the central bank. However, purchases of all kind of securities are simultaneous and it seems difficult to disentangle the effect of different types of sales. Therefore, we proceed in two steps, leveraging on the specific features of Eurosystem Quantitative Easing (QE). First, we identify the counterparts to Eurosystem purchases and estimate their relative elasticities to purchases depending on the nature of the security purchased. Second, we estimate how each type of investor rebalances upon selling any security to the Eurosystem.

The first part of the paper leverages on the diversity of asset purchase programs implemented in the EA to identify the counterparts to Eurosystem purchases depending on the type of security purchased. To do so, we put together a rich database of security-level holdings by investment sector, jointly with security-level Eurosystem asset purchases from four different asset purchase programs over 2014 Q3-2020 Q4: the third wave of the Covered Bond Asset Purchase Programs (CBPP3), the Public Sector Purchase Program (PSPP), the Corporate Sector Purchase Program (CSPP), and the Pandemic Emergency Purchase Program (PEPP). We examine heterogeneous purchases across two dimensions: by asset class - thereby assessing the impact of the different purchase programs, and by maturity. We compare holding variations in securities purchased to that of similar non-purchased securities, for the three main EA holding sectors: banks, investment funds (IF), and insurance companies and pension funds (ICPF). Identifying who sells greater shares of their holdings to the Eurosystem controlling for sector-time demand for eligible securities allows us to rank the elasticities of different sectors for each type of asset purchased. To the best of our knowledge, we are the first to explicitly estimate relative elasticities to different types of purchases, thanks to having a unique access to security-level purchase data for four different programs.

We find that banks are the most elastic EA investors for sovereign and covered bonds, while they are equally elastic to IF for corporate bonds. Due to their large market share in the former, banks end up being the largest EA sellers in volumes to CBPP3, PSPP and PEPP, while IF are the largest sellers to CSPP. ICPF appear equally elastic to IF for sovereign and covered bonds, and less elastic than both IF and banks for corporate bonds.

Across maturities, differences between sectors widen as maturity increases, and banks appear to be the sole sellers of securities of residual maturity above 15 years. The elasticity (relative to other sectors) of ICPF declines as maturity increases, while that of IF peaks

for intermediate maturities. One reason for this heterogeneity is that different types of investors have different maturity habitats. Alternatively, asset purchases may alter investors' maturity preferences. We use investor-level data to disentangle both effects, assuming each investor's preferred maturity corresponds to its mean maturity holding prior to the start of QE. IFs' behavior indeed resembles that of preferred habitat investors who are more elastic to purchases of securities further away from their habitat. This is consistent with IF being tied to a stricter form of habitat - investment mandates. On the other hand, ICPFs appear to tilt their portfolios towards higher maturities, pointing to a reach for maturity behavior.

In the second part of the paper, we estimate how different types of investors rebalance their portfolio upon selling to the Eurosystem. This amounts to focusing on the *liquidity-driven portfolio rebalancing channel* since those investors selling to the Eurosystem are the ones experiencing the substitution of debt securities by liquid assets.[3] While portfolio rebalancing may also have other causes like stealth recapitalization induced by valuation gains, our interest is to know whether who owns the securities purchased matters. Investors owning the securities purchased are directly affected by the liquidity-driven portfolio rebalancing channel, while stealth recapitalization effects depend on asset price movements which can occur even absent any asset purchase.

To proceed, we build a direct measure of asset sales by investor, which we relate to growth in holdings at the investor-security level. While investor-level asset sales are not directly observable, we infer that amount from variations in investor holdings of purchased securities at quarterly frequency. Precisely, we estimate investor-level sales to the Eurosystem in each period as the sum of security holding decreases contemporaneous to purchases of that ISIN. Our identification relies on three key features.

First, estimating asset sales is subject to both omitted variables and reverse causality biases. Regarding the former, other shocks than QE may drive a correlation between our measure of asset sales and shifts in demand. For instance, an investment fund experiencing outflows perhaps needs to reduce its holdings, including those of assets simultaneously purchased by the Eurosystem, which would look like QE led this fund to reduce its holdings. Turning to reverse causality, investors looking to downsize could tend to promote their assets to the Eurosystem, which may in turn disproportionately buy from distressed investors.[4] To circumvent this endogeneity of asset sales at the investor-level, we instrument asset sales by the investor's exposure to assets eligible for purchase in the period immediately preceding, as in Rodnyansky and Darmouni (2017) or Koetter (2020).

[3]Central bank reserves in the case of banks, or bank deposits in the case of non-banks.

[4]Eurosystem direct counterparts are always dealer banks, but ultimate sellers of securities may be from any sector.

Another concern is that investors exposed to Eurosystem purchases are disproportionately exposed to increases in asset supply from issuers. A number of papers emphasized how central bank purchases stimulated issuance of eligible securities (see Abidi and Miquel-Flores (2018) or Todorov (2020)). Here, we leverage on our granular database to control with ISIN-quarter fixed effects, to absorb any asset supply shock, in the spirit of Khwaja and Mian (2008).

Finally, a more generic concern is that exposure to central bank purchases may be correlated with other investor-level shocks that may affect demand for assets. Therefore, for each sector, we control for a (different) number of balance sheet characteristics that could indeed affect asset demand.

Different rebalancing patterns between sectors arise. Selling ICPF somewhat increase demand for non-EA debt securities, although our instrument is weaker in this analysis since there is more limited variability in ICPF asset sales. Among investment funds, investment mandates appear to dictate the extent of rebalancing. Debt funds tend to substitute the securities sold with similar types of debt securities. On the other hand, diversified funds also tend to increase demand for equities, as well as for non-EA debt securities. Finally, banks do not appear to change their demand for securities. Instead, we find evidence that banks selling to the Eurosystem increase lending over 2019 and 2020. This is consistent with papers finding that excess reserves have a positive impact on lending (Rodnyansky and Darmouni, 2017; Koetter, 2020; Kandrac and Schlusche, 2021; Christensen and Krogstrup, 2019).

Purchasing from different types of investors does not emulate demand for assets in an homogeneous manner. This has important implications for the design of central bank asset purchase programs. Central banks not only need to decide the amount of risk to remove from the market but also assess which counterparts to purchase from. Purchasing assets belonging primarily to commercial banks (as during CBPP3 or PSPP, or with purchases longer-term securities) enhances bank lending. On the other hand, purchasing primarily from investment funds (as during CSPP, or with purchases of shorter-term securities) amplifies rebalancing towards riskier assets if selling funds have flexible investment mandates.

Literature Review

We contribute to two strands of the literature.

First, we add to the literature looking at who are the counterparts to central bank asset purchases. We confirm the sectoral findings of Koijen et al. (2021) who find in the context of the first phase of the PSPP that banks were the largest EA counterpart. Unlike these authors, we however conclude that banks and not mutual funds were the most elastic

to purchases. This differs from studies in other geographies: in the UK, domestic Other Financial Institutions (OFIs) have been the largest sellers of gilts to the Bank of England (Joyce et al., 2017), while households including hedge funds were the largest sellers to the Fed (Carpenter et al., 2015). We deepen our understanding by exploring heterogeneities across programs and maturities, and estimating relative elasticities.

Second, we contribute to the literature examining portfolio rebalancing in the context of quantitative easing. The literature has adopted broadly three methods to analyze portfolio rebalancing empirically.

The first category of approaches rely on time series identification, comparing the treatment period of QE to pre-QE control periods (Bergant et al., 2020; Boermans and Vermeulen, 2018; Autrup and Jensen, 2021; Bua and Dunne, 2017), controlling for QE intensity by period (Cenedese and Elard, 2021; Joyce et al., 2017), or instead using monetary policy shocks during QE-intensive years (Bubeck et al., 2018). To identify the effect of QE, these papers assume that it is the most relevant factor affecting asset reallocation in the periods of focus, although controlling for all relevant alternative channels remains challenging.

A second group of papers uses cross-sectional heterogeneity in QE-induced valuation gains across investors. Albertazzi et al. (2020) find that affected banks increase lending (resp. purchases of risky securities) in non-vulnerable (resp. vulnerable) countries, while Paludkiewicz (2021) confirms that German banks increased lending more when they experienced higher valuation gains. These findings are however not specific to quantitative easing policies as valuation gains could be achieved with standard monetary policy instruments.

The third group of paper is closer to us and leverages on heterogeneity in exposure to the liquidity driven portfolio rebalancing channel. Several authors use the share of purchased securities held in portfolio prior to purchases as an instrument for exposure to QE. Rodnyansky and Darmouni (2017) shows that US banks more exposed to the Fed's QE programs increased lending more, while Goldstein et al. (2018) find that US mutual funds primarily rebalanced towards alternative government bonds. In Europe, Koetter (2020) shows that German banks holding securities purchased during the Securities Market Program (SMP) increased commercial lending relative to other banks. Butt et al. (2015) instead studies UK banks' exposure to OFIs' exogenous sales of securities and show that banks thus exposed to increases in reserves did not increase lending more, presumably because such deposits were deemed "flighty". Other papers examine how bank-level increases in reserves may stimulate lending in other contexts than QE (Kandrac and Schlusche, 2021; Christensen and Krogstrup, 2019). Our contribution to this group of papers is two-fold. First, we are the first to directly instrument the investor-level amount of securities sold, leveraging on our detailed dataset of Eurosystem purchases. Second, we include the three main holding sectors

and contrast rebalancing patterns across sectors in a consistent framework and emphasizing the role of investment habitat.

The paper unfolds as follows. In Section 2, we describe the multiple data sources we concatenate to build our datasets. In Section 3, we estimate relative elasticities to Eurosystem purchases depending on the type of security purchased. In Section 4, we examine how different sectors rebalance upon selling to the Eurosystem. We conclude in Section 5.

2. Data

Our analyses leverage on three granular holdings datasets: a sector-security-quarter dataset, an investor-security-quarter dataset, and a bank-firm-quarter dataset. In this section, we first describe the security-level central bank purchase data by program. This dataset is critical in allowing us to identify the heterogeneous effects of purchases, and to the best of our knowledge has not been used to this extent in previous studies. Then, we describe security-level information, and how we determine eligibility criteria to Eurosystem purchases. Finally, we describe the various sources used to build the three databases in turn.

2.1. Purchase data from the Eurosystem

Quantitative easing started mid-2014 in the EA, in a context of subdued inflation. Initially, it consisted of two programs: the Asset-Backed Securities Purchase Program (ABSPP) and the third wave of the Covered Bonds Purchase Program (CBPP3). It was significantly scaled up in 2015 Q1 to include sovereign bonds with the Public Sector Purchase Program (PSPP), and further extended with the Corporate Sector Purchase Program (CSPP) as of 2016 Q2. At the onset of the Covid-19 pandemic, a dedicated program was launched to counter its deflationary effects: the Pandemic Emergency Purchase Program (PEPP).

The Eurosystem records the transactions conducted under these programs at the security (ISIN) level with details on the amount purchased, the date of the transaction, and the program under which it is purchased. Our data spans every transaction under 4 different purchase programs, up to end-2020: CBPP3, PSPP, CSPP, and PEPP. Doing so, we cover the bulk of the Eurosystem's so-called Asset Purchase Program (APP), on top of the PEPP.[5] Figure 3.1 plots quarterly gross purchases by program over the life of the programs up to end-2020. Over this period, the Eurosystem purchased €382 bn of covered bonds under CBPP3, €2,680 bn of public debt securities under PSPP, €277 bn of corporate debt securities

[5] As of October 2022, the outstanding stock of ABSPP securities on the Eurosystem's balance sheet represents around €20 bn out of €3,260 bn total APP holdings.

under CSPP, and €730 bn of debt securities under PEPP. Additional descriptive statistics on the securities purchased (after enrichment with CSDB as discussed below) are available in Appendix Table 3.8.

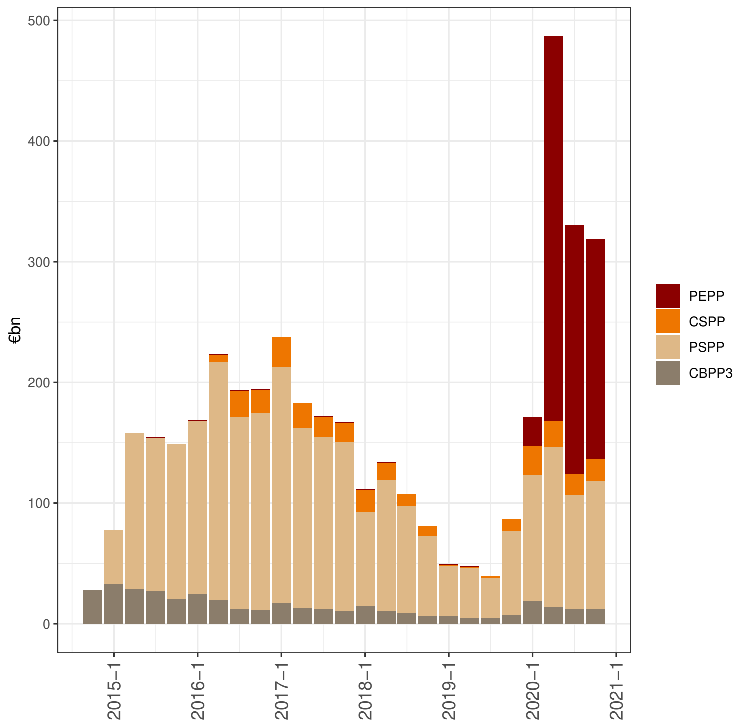


Fig. 3.1. Eurosystem purchases by program

2.2. *Security-level information*

We enrich the data with security attributes from the *Centralised Securities DataBase* (CSDB), a Eurosystem database at the security (ISIN) -month level. Among others, we add information on the issuer (sector, identifier, country), as well as the security type (e.g., covered bonds), price, face value, initial and residual maturity, and rating. Besides providing useful controls, this information is required to build eligibility criteria for the purchase programs.

Throughout the paper, we need to assess whether securities are eligible for any of the Eurosystem's purchase programs at any point in time. Eligibility criteria are shared and updated with monetary policy changes on the ECB's website. We use information available on CSDB to assess whether any given security is eligible for purchase. The effective purchase of a security overrides any conflicting information. The assessment of eligibility criteria is described in Appendix A.2.

2.3. A sector-security-quarter dataset

Sector-level security holdings are drawn from SHS-S (*Securities Holdings Statistics - Sector*). It gathers holdings at the security (ISIN) level by EA institutional sector and country, and is used by central banks to produce official financial accounts. It covers holdings of EA residents, starting in 2013 Q4.[6] Debt securities, as well as equities and fund shares, are recorded. Holdings are available both in face value and market value.

We use this dataset in the first part of the paper to estimate the relative elasticities of the different institutional sectors. We enrich SHS-S with security-level information from CSDB, and Eurosystem purchase data, as described in previous subsections.

For the purpose of our analyses, we restrict that analysis to all ISIN eligible for purchase in at least one program over 2014 Q3-2020 Q4. We focus on the three main EA holding sectors: banks, ICPF, and investment funds (other sectors hold altogether around 700 out of €6,000 bn of holdings of securities purchased at least once as of 2020 Q4 - see Table 3.9). We remove ISIN which are held well above their reported face value in CSDB.[7] We define total assets for each sector as the sum of all its security holdings in the universe of securities eligible for purchase at least once over our period of analysis. Descriptive statistics for this dataset are available in Appendix Table 3.9.

2.4. An investor-security-quarter dataset

We leverage on three different investor-level datasets, with different geographic scopes. We leverage on Banque de France's access to regulatory filings for investment funds and ICPF holdings. *OPC-titres* reports quarterly security holdings of French investment funds at the ISIN level since 2013 Q4. For ICPF, we use the S06.02 Solvency 2 (henceforth, SII) reporting template which also contains all ISIN-level security holdings of ICPF domiciled in France, starting in 2016 Q1. Finally, the Eurosystem *Securities Holding Statistics-Group* (SHS-G) registry provides holdings of securities by EA significant banking groups since 2013 Q4. The scope of SHS-G data collection comprised the 25 largest groups until 2018 Q3 when it was increased to 96 groups as a larger share of banks went under the supervision of the ECB. We collect data from these three sources until 2020 Q4 to match our Eurosystem purchase data.

We consolidate banks and insurers according to their prudential perimeters. Doing so, the analysis abstracts from intragroup holdings and splits bank-insurance conglomerates.

[6] The legal basis for collecting SHS-S data is laid down in Regulation ECB/2012/24 and subsequent amendments.

[7] Concretely, we remove all ISIN for which the sum of holdings exceeds by 20% the reported face value at least once over the sample - 2,705 ISIN in total.

Indeed, banks and insurers are subject to different legal frameworks and consequently to separate reporting and preferences even if they belong to the same conglomerate. Investment funds are left unconsolidated.

We enrich the dataset with investor-level data drawn from various sources. The national registers (*OPC-bilan* and SII) provide quarterly balance sheet information for French investment funds and insurers. These variables include total assets, cash holdings, and sector-specific variables. In particular, we use IF categories provided by *OPC-bilan* to distinguish between debt and diversified IF. Regarding banks, we collect banks' CET1 capital ratios, LCR ratios, and total assets from Bank Focus, together with non-financial private sectors deposits and central bank funding from *individual Balance Sheet Items* (iBSI), the confidential database collected by the Eurosystem to report monetary aggregates. As for SHS-S, we also augment the databases with issuer- and security-level information from CSDB, and Eurosystem purchase data.

2.5. A bank-firm-quarter dataset

To investigate whether QE stimulated bank lending, we rely on AnaCredit, a novel loan-level credit registry for the EA. AnaCredit collects harmonized data on individual loans to firms from all EA countries, and banks are required to report monthly information on all exposures above €25,000. AnaCredit reporting started in September 2018, however, the coverage was initially low, therefore we start our analyses in 2019 Q1. We restrict our attention to non-financial corporate borrowing. Borrowers and creditors are identified at the RIAD level. We consolidate creditors at the banking group level using RIAD group structures, and subsequently match each banking group to the corresponding SHS-G group - the level at which we infer asset sales to the Eurosystem. We enrich the database with the aforementioned bank-level information. Summary statistics can be found in Table 3.10.

3. Who sells to the Eurosystem?

3.1. Empirical strategy

In this section, we analyze heterogeneities in sectoral elasticities to central bank purchases. We estimate by how much each investor reduces its market share in a given security for every percentage of its face value the central bank purchases. According to preferred habitat theory, elasticities to Eurosystem purchases should differ across sectors. Arbitrageurs should have higher elasticities due to their ability to rebalance across asset classes, while

preferred habitat investors would likely display lower elasticities by lack of alternative options.

At first glance, central bank purchases appear exogenous and dictated by predetermined scopes of purchases. Once an envelope of purchases is decided, security purchases have to be proportional to National Central Banks' (NCBs) shares in the Eurosystem capital (for PSPP purchases),[8] and respect the principle of market neutrality.[9] However, the exact securities purchased by the central bank may actually be the securities pushed by investors experiencing negative demand shocks. To alleviate this concern, the estimations focus on securities eligible at least once to one of the purchase programs, and control for sector-time fixed effects, thereby capturing any shock to demand for eligible securities in a given period. In other words, our estimation measures the variation in holdings of securities purchased by the central bank relative to similar eligible securities not purchased. Then, comparing the shares of securities sold by each sector amounts to comparing price elasticities. Since all investors face the same asset prices, those selling the greatest share of their holdings for an exogenous central bank purchase shock are the most elastic.

To make sure both sides of the equation are well behaved upon issuance and redemption of securities, we normalize purchases and sales of assets by the average of securities' face value in the current and preceding quarters.[10] Since both the right- and the left-hand sides of our equation are expressed in mid-point growth rates, the coefficient of interest relates to intensive margin growth rates under the assumption of linearity. Thus, we interpret it as the percentage change in face value holdings per percentage of that security's face value purchased by the central bank.

We control for changes in each security's face value outstanding - also expressed in mid-point growth rate. This helps alleviate the concern that central banks may purchase in priority securities just issued. The time dimension of the investor-time fixed effect also controls for changes in the aggregate supply of eligible assets. Finally, we control by the change in the issuer's rating and add ISIN fixed effects. Formally, we estimate the following equation:

[8] The NCBs shares in the Eurosystem capital are calculated using a key which reflects the respective countrys' share in the total population and gross domestic product of the EA. These two determinants have equal weighting. The ECB adjusts the shares every five years and whenever there is a change in the number of NCBs that contribute to the Eurosystem capital.

[9] For instance, in its CSPP decision, the ECB specified that "A benchmark will be defined at issuer group level. The benchmark will be neutral in the sense that it will reflect proportionally all outstanding issues qualifying for the benchmark." See: `https://www.ecb.europa.eu/press/pr/date/html/index.en.html`.

[10] This is the mid-point growth rate as put forward by Davis et al. (1996), which also has the appealing side-effect of smoothing growth rates.

$$\frac{\Delta Q_{ijt}}{Q_{ijt}+Q_{ijt-1}}=\beta_i\frac{\Delta Q^{QE}_{jt}}{FV_{jt}+FV_{jt-1}}+\gamma^1\frac{\Delta FV_{jt}}{FV_{jt}+FV_{jt-1}}+\gamma^2\Delta Rating_{jt}+FE_{it}+FE_j+\epsilon_{ijt}, \quad (3.1)$$

for investor i, ISIN j, and quarter t, where ΔQ^{QE}_{jt} is the face value of security j purchased by the central bank at t, FV_{jt} the face value of security j at t, $\Delta Rating_{jt}$ a variable which increases by 1 for each drop of rating bucket using S&P standard letter scale, and Q_{ijt} the nominal holding of assets held by investor i. We express quantities in face values to abstract from the confounding effect that simultaneous price changes may have on market values.[11]

We estimate the above equation on different samples of securities using the sector-security-quarter data described in Section 2. Importantly, the comparison of elasticities across types of securities is not possible since price changes may vary across security types. We are only able to compare elasticities within specific types of asset purchases.

3.2. Across issuer types

We estimate Equation (3.1) across banks, IF, and ICPF, and compare elasticities within programs: bank covered bonds (CBPP3), government bonds (PSPP), and corporate bonds (CSPP). We reallocate PEPP purchases to those three categories of issuing sectors. Table 3.1 houses the results. Column (1) reports the estimates on the entire sample of securities eligible at least once over the sample, and further columns on subsamples of securities eligible for each program at least once over the sample.

Two main results stand out. First, banks appear to have the highest elasticity, followed by IF and ICPF. For every (mid-point) percentage of face value purchased by the central bank, banks sold roughly 1% of their face value holdings, while funds sold 0.6% and ICPF 0.2% (the t-stat associated to this coefficient is just beyond the significance threshold for ICPF). This contrasts with the findings of Koijen et al. (2021) (henceforth, KKNY) who find that mutual funds have the highest elasticity over the first part of PSPP. One can also note that all coefficients stand above -1 for government bond purchases: this is consistent with non-EA investors being the most elastic to purchases of government securities.

Second, we report heterogeneities within programs. The elasticity of ICPF to purchases of both corporate and government bonds is particularly small (consistent with KKNY who found a *negative* elasticity to PSPP purchases). IF exhibit an elasticity similar to that of banks for corporate bond purchases. In Appendix Tables 3.14 and 3.15, we test whether

[11] Several studies point to the existence of a flow effect of central bank purchases whereby purchased securities would experience a drop in yield stronger than that of similar non-purchased securities (De Santis and Holm-Hadulla, 2020; D'Amico and King, 2013). This would imply a positive bias to β_i.

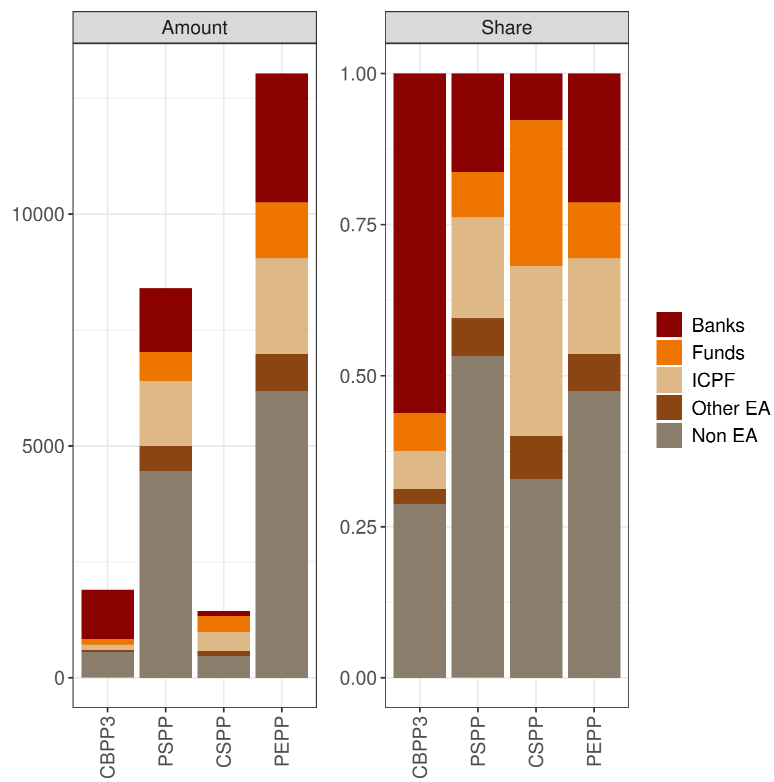
Table 3.1: Sensitivity of sectors to Eurosystem purchases

	Dependent variable:			
	All	Covered	Government	Corporate
	(1)	(2)	(3)	(4)
QE:ICPF	-0.192	-0.564***	-0.242*	-0.248*
	(0.138)	(0.200)	(0.145)	(0.147)
QE:BANK	-1.022***	-1.466***	-0.916***	-1.333***
	(0.104)	(0.195)	(0.097)	(0.207)
QE:FUND	-0.608***	-0.548***	-0.442***	-1.284***
	(0.095)	(0.150)	(0.132)	(0.159)
$\Delta FaceValue$	0.626***	0.375***	0.844***	0.640***
	(0.030)	(0.042)	(0.038)	(0.052)
$\Delta Rating$	-0.030***	-0.052***	0.002	-0.003
	(0.007)	(0.010)	(0.010)	(0.006)
Sector x Quarter FE	Yes	Yes	Yes	Yes
ISIN FE	Yes	Yes	Yes	Yes
Observations	361,265	125,131	127,080	127,806
R^2	0.113	0.105	0.106	0.149

Notes: Covered corresponds to bank covered bonds purchased in CBPP3, *Government* to government bonds purchased in PSPP, and *Corporate* to corporate bonds purchased in CSPP. PEPP purchases are reallocated to the three asset categories according to the type of asset purchased. All variables are expressed in mid-point growth rates in points (1=100%), except for $\Delta Rating$ which increases by 1 for each drop of rating bucket (using S&P standard letter scale). Standard errors are clustered at the sector-quarter and ISIN level. *p<0.1; **p<0.05; ***p<0.01.

differences between sectors are significant. Banks are indeed more elastic than ICPF across all types of securities. Banks are also significantly more elastic than IF for covered and government bonds, but the difference is not significant for corporate bonds. IF are finally significantly more elastic than ICPF only for corporate bonds.

Importantly, our method identifies relative elasticities and does not identify who effectively sold to the Eurosystem - which also depends on initial holdings of securities. Indeed, there are large heterogeneities of ownership across programs and countries. As can be seen in Figure 3.2, the securities purchased in these programs belong to different types of institutions. CBPP3 securities belong primarily to EA banks, while other securities are in majority owned by non-EA investors. Within EA investors, banks and ICPF hold the bulk of PSPP securities, while IF and ICPF hold most of CSPP securities. Ownership also differs depending on the country of issuance, as can be seen in Figure 3.4: the share of banks owning PSPP securities is particularly low in France or the Netherlands (around 10%), while it reaches almost 25% in Spain or Italy.



Notes: Total holdings of eligible securities by sector expressed in billion euros of face value (lhs) and in percentage of total face value of eligible securities (rhs).

Fig. 3.2. Holdings of eligible securities per program as of 2020Q4

Since banks were both the largest owners and the most elastic investors to purchases of

covered bonds and government bonds, they can be inferred to be the largest counterparts to the Eurosystem for these programs (consistent with KKNY). On the other hand, IF hold the bulk of corporate securities together with ICPF, but also exhibit the largest elasticity for these holdings, and thus can be expected to be the main counterparts for CSPP.

3.3. Across maturity segments

We now investigate whether the propensity of each sector to sell depends on the security's residual maturity. We re-estimate Equation (3.1), but instead of distinguishing securities by program, we distinguish them according to residual maturity brackets. Results are housed in Table 3.2.

Table 3.2: Sensitivity of sectors to purchases by maturity

	Dependent variable:			
	0-5	5-10	10-15	15-100
	(1)	(2)	(3)	(4)
QE:ICPF	-0.414**	-0.165	0.041	0.380
	(0.164)	(0.126)	(0.186)	(0.352)
QE:BANK	-0.977***	-0.706***	-1.538***	-1.289***
	(0.128)	(0.078)	(0.280)	(0.401)
QE:FUND	-0.448***	-0.689***	-0.855***	-0.109
	(0.104)	(0.127)	(0.189)	(0.278)
$\Delta FaceValue$	0.611***	0.607***	0.604***	0.601***
	(0.029)	(0.029)	(0.029)	(0.029)
$\Delta Rating$	-0.030***	-0.030***	-0.030***	-0.030***
	(0.007)	(0.007)	(0.007)	(0.007)
Sector x Quarter FE	Yes	Yes	Yes	Yes
ISIN FE	Yes	Yes	Yes	Yes
Observations	361,265	361,265	361,265	361,265
R^2	0.112	0.112	0.112	0.112

Notes: Columns correspond to purchases of securities from brackets of residual maturity of purchased securities. All variables are expressed in mid-point growth rates in points (1=100%), except for $\Delta Rating$ which increases by 1 for each drop of rating bucket (using S&P letter scale). Standard errors are clustered at the sector-quarter and ISIN level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Only banks appear to sell long-term securities above 15 years. The gap between the elasticity of ICPF and banks widens with maturity, driven by growing coefficients for ICPF.

The elasticity of funds seems to be closer to that of banks for intermediate maturities and is non-significant for higher maturities.

Comparing the dispersion of elasticities across different types of purchases is possible as long as the central bank purchases similar shares of securities in each group. Indeed, all estimates β_i tend to converge to -1 when central bank purchases get closer to the full securities' face value. However, as discussed above, one cannot directly compare elasticities across maturity segments, as these depend on how prices changed within each segment. Our main results pertain to relative elasticities within each maturity segment.

There are two reasons why sectors may behave differently across maturities. First, sectors could have structurally different maturity habitats. The other possibility is that asset purchase programs heterogeneously affect sectors' relative preference for assets of different categories. As can be observed in Appendix Figure 3.5, the distribution of holdings by residual maturity differs across sectors which points to the existence of different maturity habitats (see also Figure 3.6 in the Appendix). ICPF market share increases for securities with higher residual maturities. Banks have a higher market share in shorter and longer maturities, while funds occupy a stable market share across maturities.

To explore this question further, we leverage on holdings data at the investor level to test whether, within sector, investors sell in priority securities whose maturity is farther away from their habitat - or whether the residual maturity itself determines the propensity to sell. We build a measure of maturity habitat by investor - defined as the weighted average residual maturity of government securities held by each investor prior to the start of QE. For ICPF for which we do not have granular data before 2016, we use the weighted average maturity of securities held in the pooled distribution of holdings as a proxy. Then, we construct an ISIN-investor-quarter specific distance to maturity $DistMat_{ijt}$ that corresponds to the absolute value of the difference between security j's residual maturity at t and investor i's maturity habitat, standardized by the standard deviation of maturities held by each sector prior to QE. Formally, we estimate the following equation:

$$\frac{\Delta Q_{ijt}}{Q_{ijt} + Q_{ijt-1}} = \beta_i \frac{\Delta Q_{jt}^{QE}}{FV_{jt} + FV_{jt-1}} \times |DistMat_{ijt}| + \gamma_i \frac{\Delta Q_{jt}^{QE}}{FV_{jt} + FV_{jt-1}} \times Mat_{jt} + X_{ijt} + \epsilon_{ijt}, \tag{3.2}$$

for investor i, security j, and quarter t, where X_{ijt} contains all variables as in Equation (3.1), as well as the individual terms from the interaction term that are not displayed for convenience.

Results are housed in Table 3.3. Only IF tend to behave like preferred habitat investors,

Table 3.3: Sensitivity of sectors to Eurosystem purchases by distance to maturity

	Dependent variable:		
	ICPF	Banks	Funds
	(1)	(2)	(3)
QE	-0.092	-1.067***	-0.608***
	(0.103)	(0.128)	(0.091)
QE:|Distance to maturity|	-0.137	0.011	-0.144***
	(0.090)	(0.104)	(0.050)
QE:Residual Maturity	0.030**	0.010	-0.003
	(0.013)	(0.013)	(0.009)
|Distance to maturity|	0.003**	-0.003	-0.007***
	(0.001)	(0.002)	(0.001)
$\Delta FaceValue$	0.323***	0.346***	0.517***
	(0.024)	(0.026)	(0.025)
$\Delta Rating$	-0.008**	0.001	-0.007**
	(0.003)	(0.005)	(0.003)
Sector x Quarter FE	Yes	Yes	Yes
ISIN FE	Yes	Yes	Yes
Observations	258,779	922,908	2,544,982
R^2	0.200	0.020	0.064

Notes: Standard errors are clustered at the investor-quarter and ISIN level. Distance to maturity corresponds to the standardized difference in years between the residual maturity of the security and the pre-APP mean residual maturity of eligible debt securities held by the investor. Pre-APP is understood as pre-2014 Q4 for banks and funds, and as 2016 Q1 for ICPF. Distance to maturity is winsorized at 0.5% on both sides. The dependent variable, QE and face value growth are all expressed in mid-point growth rategs (1=100%), while $\Delta Rating$ increases by 1 for each drop of rating bucket (using S&P letter scale). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

and sell more securities that are further away from their maturity habitat. This is consistent with investment funds facing the strictest constraints in the form of investment mandates. ICPFs are close to displaying a preferred habitat behavior, but the negative coefficient β_i is associated with a p-value just above 10%. Finally, banks do not appear to display any behavior consistent with a preferred habitat.

The coefficient on securities' maturity must be taken with caution for reasons already mentioned. Price movements may vary across security types in which case one cannot compare β_i across securities. For instance, if one sector is less elastic to purchases of high-maturity securities, their price may increase more, prompting other sectors to sell more of those assets even if they are equally elastic across maturities. To the extent that high-maturity securities experience a stronger price growth on average in our sample (see Figure 3.7 in Appendix), the positive coefficient on maturity for ICPF is conservative and suggests that ICPF reach for maturity.

4. How do investors rebalance upon selling?

4.1. Empirical strategy

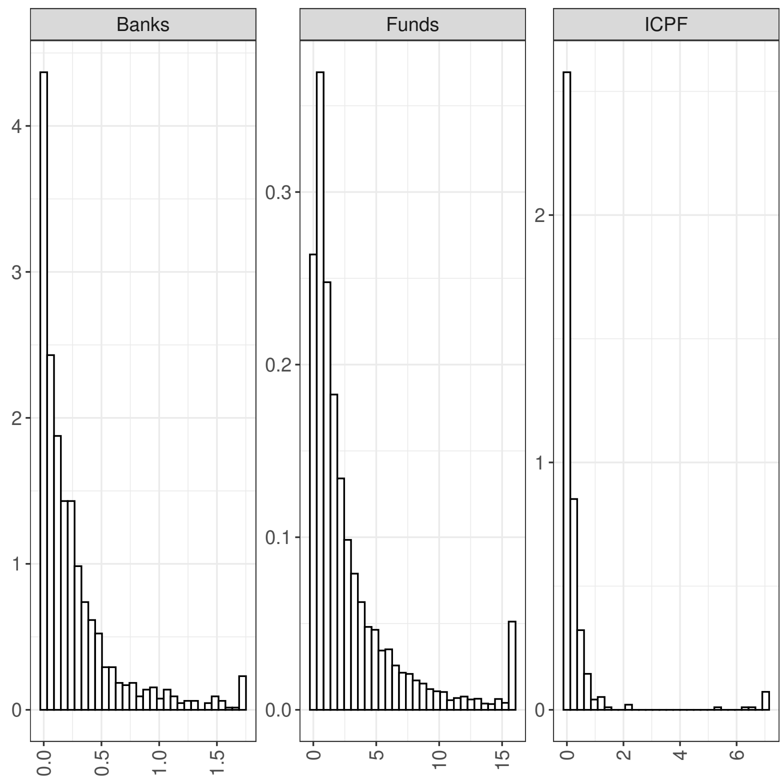
We now investigate how investors heterogeneously rebalance their portfolio upon selling to the Eurosystem. To do so, we build a measure of asset sales by investor and show that investors increase demand for assets in a heterogeneous manner upon selling to the central bank. Again, preferred habitat theory yields predictions on how investors rebalance their portfolios upon selling their assets to the Eurosystem. While arbitrageurs may actively increase their demand for alternative assets, preferred habitat investors may on the other hand try to substitute the assets they sell with similar non-purchased assets.

Since we do not observe investors' sales of securities to the Eurosystem, we infer that amount from variations in investors' holdings of purchased securities at a quarterly frequency. Precisely, we estimate their sales to the Eurosystem as all negative security holding variations contemporaneous to purchases of that security by the Eurosystem. We restrict the measure to negative security holding variations as the Eurosystem did not taper its purchases over the course of the period studied. Hence, Eurosystem activities are not expected to have caused any increase in holdings of purchased securities and we can restrict our variable of interest to negative holdings variations to increase the precision of our estimates. Formally:

$$\Delta Q_{it}^{SOLD} = \sum_j \Delta Q_{ijt} \times \mathbb{1}\{\Delta Q_{ijt} < 0\} \times \mathbb{1}\{\Delta Q_{jt}^{QE} > 0\}, \tag{3.3}$$

with ΔQ_{ijt} the quarterly variation in security j face-value held by investor i. This approach may seem rather conservative. As a non-negligible share of purchases target securities is issued in the same quarter, investors could increase their holdings, but less than they would have had if no central bank purchase had been conducted (as in Bubeck et al. (2018)). However, our approach seems more suitable to study the liquidity channel of QE, which operates when investors strictly reduce their holdings of purchased securities.

Figure 3.3 plots the distribution of total asset sales by investor, with each quadrant focusing on a specific sector. As expected, total sales represent small shares of banks and insurers' large balance sheets, while the tail of the distribution is fatter for IFs which can have smaller balance sheets.



Notes: Asset sales pooled across investors and quarters. Expressed in pp, right-winsorized at 1% by sector.

Fig. 3.3. Distribution of investor-level non-null asset sales by sector

There are three challenges to identifying the causal effect of asset sales on increased demand for alternative assets from investors. First, our measure of asset sales is subject to both omitted variables and reverse causality bias. To begin with the former, investors subject to negative shocks (e.g., unexpected losses, fund shares redemption) may need to reduce their balance sheet exposures, thereby jointly decreasing asset demand and apparently selling assets to the Eurosystem. The reverse causality problem lies in the fact that investors

looking to downsize might promote their assets to the Eurosystem, who could in turn be over-purchasing securities held by investors experiencing negative shocks. Within pre-defined purchase perimeters, central banks may thus purchase larger shares of securities pushed by investors looking for divestment opportunities. To circumvent both issues, we instrument asset sales by the share of assets eligible for purchase on each investor's balance sheet in the preceding quarter - in the spirit of previous work by Rodnyansky and Darmouni (2017) and Koetter (2020).

A second challenge relates to the fact that those investors more exposed to eligible securities may also be specialized in certain types of assets whose supply is more elastic to central bank purchases. For instance, if central bank purchases stimulate government bond security issuance, then investors holding large shares of government bonds will face a stronger increase in asset supply. Here, we leverage on our granular data to implement and extend the Khwaja and Mian (2008) approach of factoring out loan demand by using borrower-quarter fixed effects. We extend the approach by using security-quarter fixed effects to factor out demand for securities. Our estimates use the fact that multiple investors differently affected by central bank purchases increase their holdings of securities to a varying degree.

Third, omitted variables correlating with the instrument, holdings of eligible assets, may affect asset demand over the period of concern. For instance, banks with low shares of eligible assets may have been more inclined to draw on TLTRO III credit lines that were launched in 2019, thereby confounding the effect of quantitative easing. To address this concern, we include a host of quarter-lagged investor-specific controls. Specifically, we control for the total assets (in logarithm) and total asset growth in all specifications. We also control for cash ratios (as a percentage of total assets) for investment funds and ICPF, while controlling for the Liquidity Coverage Ratio (LCR) for banks to capture the liquidity of investors' assets. For solvency, we control with the Solvency Capital Ratio (SCR) for ICPF and the CET1 capital ratio for banks, which are the standard measures of regulatory leverage in their respective sector. We add a control for non-financial private sector deposit growth and for contemporaneous growth in central bank funding - which includes potential usage of TLTRO III. Finally, we add the lagged asset sales in all equations to account for the autocorrelated nature of the variable of interest.

We now turn to our empirical specification. We seek to show how investors selling more to the Eurosystem increase demand for certain types of securities more. We estimate the following regression for each institutional sector (banks, IF, and ICPF) and different asset types A at the investor-security-quarter level:

$$\frac{\Delta Q^{A}_{ijt}}{Q^{A}_{ijt}} = \beta_i \times \frac{\Delta Q^{SOLD}_{it}}{TA_{it-1}} + X_{it} + FE_{jt} + \epsilon_{ijt}, \tag{3.4}$$

for investor i, security j, and quarter t. The subscript A refers to any asset type including equities, fund shares, non-purchased debt securities, and subcategories of debt securities. For instance, we estimate whether demand for high-yield debt securities increases more for banks selling more to the Eurosystem. As made clear previously, $\frac{\Delta Q^{SOLD}_{it}}{TA_{it-1}}$ is instrumented by the lagged share of eligible assets on investor i's balance sheet. X_{it} contains all controls aforementioned. Since the dependent variable is a growth rate, it is only defined over pre-existing holdings of securities and does not capture investors' entry onto new positions. Finally, we weight equations by lagged exposures in a weighted least squares (WLS) setting. This allows us to interpret our coefficients more naturally as the growth rate in holdings of a certain type of security upon selling to the Eurosystem.

Importantly, we focus on active rebalancing and abstract from passive rebalancing - variations in market values merely resulting from marking to market assets in an environment of changing monetary policy. Active rebalancing consists in reductions in the face value of holdings, hence Q^{A}_{ijt} is expressed in face value. For equities and fund shares, it is expressed in number of shares.

As asset sales are positive by definition, a positive coefficient suggests that there is rebalancing towards a given asset class, while a negative coefficient implies that holdings of that class were reduced in tandem with asset sales. In regression tables, we report robust Kleibergen-Paap (henceforth, KP) F-statistics (Kleibergen and Paap, 2006), and verify that they are above the standard threshold of 10 to relegate weak instrument concerns (Staiger and Stock, 1997).[12]

4.2. Rebalancing across securities

We first estimate Equation (3.4) for ICPF. Results are presented in Table 3.4. Unfortunately, KP F-statistics are lower than 10, which raises concerns over the strength of our instrument. Since ICPF tend to be less elastic to Eurosystem purchases, asset sales display less variability which the instrument struggles more to capture. Our results on ICPF must therefore be interpreted with caution. First stage estimations are presented in Table 3.16 in Appendix.

ICPF selling to the Eurosystem tend to increase demand for non-EA debt securities. Demand for all other types of assets remains unchanged, although rebalancing to high-yield

[12]More precisely, according to Table 2 in Stock and Yogo (2005), to limit the size of our 5% Wald test to 10%, F-statistics need to remain above 16.

debt is almost significant, with a p-value of 0.102. Quantitatively, for every percentage of total assets sold, ICPF increase their growth rate of non-EA debt securities holdings by 3.1 pp. Apart from that and as could have been expected, we do not detect major shifts in demand across ICPF.

Table 3.4: Effect of asset sales on securities growth, ICPF

	Portfolio share growth						
	Debt	Equities	Fund shares	EA Debt	Non-EA Debt	IG Debt	HY Debt
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Asset Sales	-16.401	-3.407	-1.437	-19.583	3.107**	-1.167	21.930
	(14.089)	(5.965)	(3.208)	(13.656)	(1.580)	(2.125)	(13.368)
Asset Sales Lag	-1.815	-0.020	-0.026	-3.215	-0.204**	-0.436*	0.005
	(1.407)	(0.137)	(0.149)	(2.346)	(0.088)	(0.249)	(0.044)
Total Assets Growth Lag	-0.711	0.210	-0.273	-0.810	-0.056	-0.095	-0.002
	(0.500)	(0.209)	(0.252)	(0.500)	(0.086)	(0.098)	(0.218)
Total Assets Lag	0.654*	-0.892	-0.437	1.158**	0.473**	0.462***	-0.641
	(0.375)	(0.628)	(0.495)	(0.509)	(0.210)	(0.120)	(0.587)
SCR Ratio Lag	-1.677	-1.944**	-0.387	-2.570	0.410	0.295	-1.616
	(1.588)	(0.793)	(1.105)	(1.730)	(0.299)	(0.383)	(1.516)
Cash Ratio Lag	0.064	-0.361	-1.030**	0.533	0.024	-0.039	-0.287
	(0.247)	(0.308)	(0.458)	(0.397)	(0.129)	(0.091)	(0.398)
Kleibergen-Paap F-stat	2.54	1.9	3.65	2.29	3.42	2.31	3.18
ISIN x Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	340,426	189,299	795,472	136,557	203,869	267,398	22,279
R^2	0.890	0.824	0.752	0.769	0.968	0.914	0.948

Notes: Standard errors are clustered at the investor-quarter and ISIN level. *Asset sales* are instrumented by the lagged share of assets eligible on ICPF' balance sheet. They are expressed in percentage points of ICPF lagged total assets. The dependent variable is expressed in percentage (1 = 1%) and right-winsorized at 2.5%. All growth rates and ratios are expressed in percentage of lagged total assets. Growth rates are all winsorized at 1% on both sides. Coefficients are weighted by holdings market value for shares and fund-shares or nominal value for debt. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

KP F-statistics for banks are well above the weak instrument threshold. Table 3.17 displays the first stage estimates. They show that for every percentage of eligible assets in their portfolio at t-1, banks sell 2 to 4 basis points worth of assets to the Eurosystem in any quarter. The final results for banks are displayed in Table 3.5. Banks selling to the Eurosystem do not tend to alter demand for any type of security. In the next subsection, we will examine how bank lending reacts to asset sales.

KP F-statistics for investment funds are all well above the required thresholds, except for the equation involving equities which is just above 10. Table 3.18 displays the first stage estimates which are of the same order of magnitude as for banks. To emphasize the role played by funds' habitat, we differentiate funds by their type: debt, diversified, and *other*

Table 3.5: Effect of asset sales on securities growth, banks

	Portfolio share growth						
	Debt	Equities	Fund shares	EA Debt	Non-EA Debt	IG Debt	HY Debt
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Asset Sales	6.149	1.356	0.287	7.459	4.737	7.160	-14.909
	(4.534)	(26.393)	(20.670)	(4.807)	(7.950)	(4.989)	(11.054)
Asset Sales Lag	-4.938	8.980	7.205	-5.486*	-4.079	-5.199	10.212
	(3.351)	(14.678)	(12.451)	(3.247)	(6.118)	(3.450)	(8.469)
Total Assets Growth Lag	0.229	0.805	0.706	0.220	0.243	0.083	2.008*
	(0.204)	(1.289)	(1.468)	(0.240)	(0.266)	(0.215)	(1.125)
Total Assets Lag	-1.945***	8.692**	10.708***	-1.459**	-2.751***	-1.730***	-6.648***
	(0.494)	(3.721)	(3.217)	(0.596)	(0.621)	(0.521)	(2.264)
CET1 Ratio Lag	0.391***	-0.409	-4.244*	0.446***	0.296*	0.374**	-1.600
	(0.142)	(1.520)	(2.463)	(0.164)	(0.163)	(0.145)	(1.255)
LCR Ratio Lag	0.004	0.171	0.062	0.004	0.014	0.008	-0.049
	(0.018)	(0.141)	(0.104)	(0.021)	(0.028)	(0.020)	(0.046)
NFPS Deposit Growth Lag	-0.103	-0.733	-0.029	-0.202	0.015	-0.013	-0.550
	(0.174)	(0.800)	(0.828)	(0.189)	(0.240)	(0.178)	(1.276)
Central Bank Funding Growth Lag	21.993	-433.525	15.104	-1.186	39.970	-7.170	-59.148
	(35.149)	(358.756)	(162.248)	(34.664)	(50.685)	(32.365)	(251.146)
Kleibergen-Paap F-stat	66.47	30.1	37.27	70.73	39.73	58.69	50.16
ISIN x Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	951,410	902,757	246,033	519,950	431,460	442,262	51,210
R^2	0.642	0.907	0.862	0.645	0.635	0.551	0.688

Notes: Standard errors are clustered at the investor-quarter and ISIN level. *Asset sales* are instrumented by the lagged share of assets eligible on banks' balance sheet. They are expressed in percentage points of banks lagged total assets. The dependent variable is expressed in percentage (1 = 1%) and right-winsorized at 2.5%. All growth rates and ratios are expressed in percentage of lagged total assets. Growth rates are all winsorized at 1% on both sides. Coefficients are weighted by holdings in market value for shares and fund-shares or nominal value for debt. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

funds.[13] Indeed, we found in the previous section that funds behaved like preferred habitat investors by sticking to maturity mandates. We hypothesize that debt funds tend to have stricter investment mandates, and will thus be less able to increase demand for equities.

The results are housed in Table 3.6 and confirm this intuition. Diversified funds selling to the Eurosystem tend to increase their demand for equities, unlike debt funds. For every percentage of total assets sold, diversified funds increase their growth rate of equity holdings by 1.8 pp. Diversified funds also appear to increase demand for non-EA issued debt securities. Conversely, debt funds tend to increase demand only for debt securities which are closest to those actually purchased (investment grade and EA-issued), and even reduce demand for high-yield debt securities. This suggests these funds have stricter mandates even over debt and tend to substitute the securities they sell with similar securities.

Table 3.6: Effect of asset sales on securities growth, funds

	Portfolio share growth						
	Debt	Equities	Fund shares	EA Debt	Non-EA Debt	IG Debt	HY Debt
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Asset Sales: Debt funds	1.958***	4.030	1.646	2.614***	1.146	2.538***	-5.927***
	(0.517)	(4.230)	(1.213)	(0.599)	(0.743)	(0.605)	(1.854)
Asset Sales: Diversified funds	6.503***	1.800*	0.202	6.536***	4.766**	5.427***	-4.387
	(1.706)	(0.969)	(1.201)	(1.520)	(1.959)	(1.468)	(3.586)
Asset Sales: Other funds	4.195**	0.910	-0.914	3.625*	6.107***	5.166**	4.284
	(1.696)	(0.681)	(1.651)	(2.015)	(1.882)	(2.119)	(5.736)
Kleibergen-Paap F-stat	128.17	10.14	27.52	94.41	131.85	98.28	34.18
ISIN x Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	934,735	808,537	243,502	567,847	366,888	661,603	110,538
R^2	0.580	0.424	0.446	0.285	0.761	0.393	0.342

Notes: Standard errors are clustered at the investor-quarter and ISIN level. *Asset sales* are instrumented by the lagged share of assets eligible on funds' balance sheet. They are expressed in percentage points of funds lagged total assets. The dependent variable is expressed in percentage (1 = 1%) and right-winsorized at 2.5%. All growth rates and ratios are expressed in percentage of lagged total assets. Growth rates are all winsorized at 1% on both sides. Coefficients are weighted by holdings market value for shares and fund-shares or nominal value for debt. Coefficients on all controls except the variables of interest have been hidden for convenience. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

In a nutshell, different patterns seem to appear across sectors and could be interpreted through the lens of PH theory: investors selling assets to the Eurosystem rebalance towards other asset classes that are part of their habitat. Investment funds with strict mandates (e.g., debt funds) increase demand for non-purchased eligible debt securities, while investment funds with more flexible mandates (e.g., diversified funds) also increase demand for alternative debt securities and equities. In the next sub-section, we finally study whether asset purchase programs stimulate bank lending.

[13]We mainly keep *other* funds to improve the estimation of demand for securities financing through our security-quarter fixed effects.

4.3. Bank lending

In this subsection, we ask whether QE led to increased lending by banks through the liquidity-driven portfolio rebalancing channel.

We implement a similar method to the one from the previous subsection, this time using Anacredit loan-level data (see Section 2). One limitation is that the Anacredit reporting only started in late 2018. Our sample is thus restricted to 2019 and 2020, which are specific years. Purchases were lower over 2019 and even halted in net terms in the last part of the year: this implies that QE shocks were substantially smaller over that period. Then, lending growth was particularly strong and unusual in 2020 due to the COVID pandemic, which prompted most European governments to settle loan guarantee schemes that strongly supported credit supply. While there is no reason to believe this should be correlated to holdings of eligible assets, it calls for caution in interpreting results.

We estimate the following weighted least square equation:

$$\frac{\Delta Loan_{ijt}}{Loan_{ijt-1}} = \beta \times \frac{\Delta Q_{it}^{SOLD}}{TA_{it-1}} + X_{it} + FE_{jt} + \epsilon_{it}, \tag{3.5}$$

using the same controls and notations as in the previous subsection, except for j which now denotes a borrower. As detailed in the data section, we aggregate our loan-level data at the lender-borrower-quarter level. As in the previous subsection, we instrument $\frac{\Delta Q_{it}^{SOLD}}{TA_{it-1}}$ by the lagged share of assets eligible for purchase on banks' balance sheets.

We first verify that KP Wald tests are high enough in the instrumented regressions, and show the results of the first-stage estimates in Table 3.19. The share of assets eligible for purchase is highly correlated to asset sales by banks, with every basis points of eligible assets on banks' balance sheets associated to approximately 0.03 bps of total assets sold to the Eurosystem in a given quarter.

Results are presented in Table 3.7 and show that QE indeed stimulates bank lending. For every additional percentage of total assets sold by a bank, it increases lending growth by 3.7 pp relative to other banks. In Appendix Table 3.10, one can see that the third quartile of asset sales stands at 0.25% in our sample, and is zero for the first quartile. Hence, our results imply that the most affected banks (those at the third quartile of selling) increase lending growth by roughly 1 pp more than non-affected banks (those at the first quartile of selling).

In Column (2), we estimate the same equation without instrumenting asset sales. As could have been expected, the coefficient becomes significantly smaller and insignificant. Indeed, the effect of QE is no longer identified and is confounded with negative shocks that banks may simultaneously be experiencing. In Column (3), we do not weight equations, and

use a simple OLS setup. The coefficient is significantly larger than in Column (1), suggesting that banks expand primarily through smaller exposures.

In Column (4), we add bank-specific valuation gains as control. As in Albertazzi et al. (2020), we define valuation gains as the passive quarterly gains attributable to changes in asset prices at constant portfolio weights. Formally:

$$ValGains_{it} = \sum_{j} \Delta P_{jt} \omega_{ijt-1}, \tag{3.6}$$

Albertazzi et al. (2020) found that investor-level valuation gains between 2014 Q1 and 2015 Q2 led to higher lending by banks located in non-vulnerable countries, thereby suggesting stealth recapitalization effects were at play. Crucially, their identification hinged on valuation gains being mainly driven by QE over that period. Valuation gains do not appear to be driving any increase in loan supply over 2019-2020, perhaps because QE was not a major driver of price changes over that period - which was largely affected by the COVID shock.

Finally, our estimations confirm the relevance of some controls in explaining loan supply: larger banks and banks with higher CET1 capital ratios tend to lend more.

5. Conclusion

In this paper, we show that central bank asset purchase programs do not have the same effect on portfolio rebalancing depending on the type of securities purchased. We show that who initially holds the securities purchased matters.

First, we show that different types of purchases are accommodated by different types of investors. Among EA investors, sovereign debt securities and bank covered bonds are primarily sold by banks who are both the most elastic to purchases and the largest holders of such securities. IF are the largest sellers of corporate securities as they exhibit similar elasticities to banks, together with larger initial holdings. Across maturities, we find that investment funds tend to exhibit some preferred habitat behavior and are less elastic to purchases of securities closer to their maturity habitat, while there are signs that ICPF are reaching for maturity.

In the second part of the paper, we show that different types of investors rebalance differently upon selling to the Eurosystem. Banks selling to the Eurosystem tend to increase lending. ICPF marginally increase their demand for non-euro area debt securities. Funds with flexible mandates tend to increase demand for all types of debt securities and equities, while less flexible funds tend to substitute the securities sold with similar securities.

Table 3.7: Effect of asset sales on loan growth

	2-stage WLS (1)	WLS (2)	2SLS (3)	ValGains (4)
Asset Sales	3.718*	0.547	8.928**	3.771*
	(2.203)	(0.501)	(3.997)	(2.263)
Asset Sales Lag	-1.194	0.492	-3.259	-1.216
	(1.518)	(0.592)	(2.605)	(1.538)
Total Assets Lag	0.654**	0.611**	1.036**	0.644**
	(0.313)	(0.283)	(0.510)	(0.320)
Total Assets Growth Lag	-0.097	0.014	-0.053	-0.100
	(0.138)	(0.102)	(0.236)	(0.142)
CET1 Ratio Lag	0.294*	0.302*	0.654***	0.295*
	(0.163)	(0.161)	(0.209)	(0.163)
LCR Ratio Lag	-0.008	-0.009	0.009	-0.008
	(0.011)	(0.011)	(0.014)	(0.012)
NFPS Deposit Growth Lag	0.168*	0.154*	-0.099	0.172*
	(0.095)	(0.084)	(0.148)	(0.096)
Central Bank Funding Growth	0.080	0.080	0.236	0.080
	(0.227)	(0.223)	(0.288)	(0.228)
Valuation Gains				-0.337
				(0.790)
Num.Obs.	6185245	6185245	6185245	6185245
Adj. R2	0.03	0.1	0.1	0.1
Kleibergen-Paap Wald test	15.31		14.05	13.31
Firm-quarter FE	Yes	Yes	Yes	Yes

Notes: Standard errors are clustered at the bank-quarter and firm level. In columns (1), (3), and (4) asset sales are instrumented by the lagged share of assets eligible on banks' balance sheet. Asset sales are expressed in percentage points of banks lagged total assets. The dependent variable is expressed in percentage (1 = 1%) and right-winsorized at 2.5%. All growth rates and ratios are expressed in percentage of lagged total assets. Growth rates are all winsorized at 1% on both sides. Column (1) corresponds to the baseline instrumented 2-stage WLS estimation. Column (2) corresponds to the non-instrumented WLS regression. Column (3) corresponds to a 2 stage OLS regression without weighting. In column (4) we use the baseline instrumented 2-stage WLS regression with added bank-level valuation gains as control. *p<0.1; **p<0.05; ***p<0.01.

Our findings have important implications for the design of central bank asset purchase (and divestment) programs. Beyond the amount of risk that the central bank decides to bear, the structure of asset demand for the securities purchased will matter for monetary policy transmission and potential financial stability spillovers.

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A. Data cleaning

A.1. CSDB

The EA Centralized Securities Database (CSDB) comprises information on all the following types of securities: (1) securities issued by EU residents; (2) securities likely to be held and transacted by EU residents; (3) securities denominated in euro, whoever the issuer is and wherever they are held. The data is compiled at a monthly frequency. We use this registry to extract security-level attributes to merge with holdings data.

The computation of debt securities price and face value outstanding deserves further details. Following CSDB classification, we distinguish two categories of debt securities. The standard type of debt security excludes structured debt securities (primary asset class D.18) quoted in price per share (quotation basis type CCY). In this case, face value and prices are provided directly. For structured debt securities quoted in price per share, prices and accrued interests have to be normalized by the issue price of the debt security, and face value is computed as the ratio of market value over the instrument's sum of price and accrued interests. We convert non-euro securities prices using quarter-end exchange rates published on the Banque de France website. We take the conservative step to set prices and face values to null when prices are outside the 0.2-3 range - to avoid keeping securities quoted in price per share (instead of price per unit of debt face value).

CSDB also reports ratings from four rating agencies: Standard and Poor's, Moody's, Fitch, and DBRS Morningstar. We follow the Eurosystem priority rule of bond rating against issuer rating and consider the averaged rating if several agencies rate the issue. We convert ratings in probabilities of default by first mapping ratings into Credit Quality Steps, and further converting Credit Quality Steps into 3-years probabilities of default using guidelines provided by the European Banking Authority.[14]

A.2. Eligibility criteria

We apply ECB criteria as described and updated on the ECB website for each security in our datasets.[15] The common denominator of all eligible securities is that they are debt securities issued by EA issuers (including supranational institutions), in euro.

CBPP3 eligibility is restricted to covered bonds issued by credit institutions. Covered bonds are identified as such in CSDB, but a number of purchased securities happen to be

[14] See Joint Final draft Implementing Technical Standards on the mapping of ECAIs' credit assessment.

[15] See `https://www.ecb.europa.eu/mopo/implement/app/html/index.en.html` for the APP, and `https://www.ecb.europa.eu/mopo/implement/pepp/html/index.en.html` for the PEPP.

reported as traditional securitizations, therefore we also add the latter category to our scope. Issuers must be investment-grade, and there is no maturity restriction.

PSPP eligible comprises public sector debt securities, issued by investment-grade issuers. The security's residual maturity must be strictly lower than 31 years. Initially, purchases were restricted to securities with residual maturity over 2 years. The threshold was decreased to 1 year in 2017 Q1.

CSPP covers investment-grade debt securities issued by corporates other than credit institutions, with a residual maturity strictly inferior to 31 years, and above 6 months. In 2020 Q1, the criteria was loosened to 28 days for securities with an initial maturity below 1 year. Commercial paper must have an outstanding value above €10 mn. 8 specific state-owned enterprises were initially purchased by PSPP, and entered the investment universe of CSPP once CSPP purchases started.

PEPP includes all previous securities and broadens eligibility along two dimensions: sovereign bonds issued by Greece become eligible under the PEPP (although they are not investment-grade), and the lower bound for residual maturity is set to 70 days (except for securities with an initial maturity below 1 year and a residual maturity above 28 days which remain eligible as in CSPP).

In case a security is purchased and not identified as eligible according to our criteria (either because data is missing, or because of data quality issues), we automatically consider it as eligible. Finally, we fill eligibility missing values with surrounding values. We also fill eligibility backwards (forward) using the first (last) non-missing value, provided the purchase program at stake was active in the period of retropolation.

B. Descriptive statistics

Table 3.8: Descriptive statistics - purchase data

Programme	N.ISIN	Amount	Residual Maturity			PD	Face value		
		€bn		*yrs*		*%*		*€bn*	
	Count	Sum	Q25	Q50	Q75	Q50	Q25	Q50	Q75
CBPP3	1328	382	3.00	4.90	7.10	1.40	0.50	1.00	1.25
PSPP	2209	2680	3.70	6.40	9.90	1.50	1.00	3.65	14.08
CSPP	1959	277	3.60	6.00	8.40	2.50	0.50	0.70	1.00
PEPP	2630	730	2.30	5.30	9.10	1.70	0.75	1.50	8.60
Total	6065	4068	3.30	5.70	8.70	1.80	0.60	1.00	3.00

Table 3.9: Holdings of securities purchased and eligible by sector and programme

Variable	Programme	All	Banks	Funds	ICPF	HH	MMF	OFI	Other
N.ISIN	All - Purchased	5561	5467	5430	5283	4788	1651	4160	5129
Amount	All - Purchased	6083	1840	1185	2288	136	54	69	490
N.ISIN	All - Eligible	31637	18355	15281	13264	7516	9344	6894	9192
Amount	All - Eligible	7825	2975	1368	2547	182	130	81	516
N.ISIN	CBPP3 - Purchased	1288	1287	1271	1221	1123	389	859	1199
Amount	CBPP3 - Purchased	363	153	83	94	3	1	3	26
N.ISIN	CBPP3 - Eligible	10692	8021	5115	4039	1800	588	1772	2228
Amount	CBPP3 - Eligible	1400	1090	125	137	4	4	10	29
N.ISIN	PSPP - Purchased	2084	2068	2023	1952	1711	568	1428	1884
Amount	PSPP - Purchased	4670	1510	745	1795	115	7	54	424
N.ISIN	PSPP - Eligible	6310	4946	3418	3899	2369	1053	2009	2835
Amount	PSPP - Eligible	5155	1711	822	1919	153	29	59	442
N.ISIN	CSPP - Purchased	1926	1911	1922	1924	1855	502	1730	1901
Amount	CSPP - Purchased	737	78	277	334	16	4	6	20
N.ISIN	CSPP - Eligible	13525	4935	6445	5112	3235	6985	2994	3994
Amount	CSPP - Eligible	1091	122	390	465	23	50	9	29
N.ISIN	PEPP - Purchased	2275	2207	2212	2162	1911	450	1674	2080
Amount	PEPP - Purchased	5098	1559	925	1920	117	49	60	448
N.ISIN	PEPP - Eligible	31637	18355	15281	13264	7516	9344	6894	9192
Amount	PEPP - Eligible	7825	2975	1368	2547	182	130	81	516

Notes: Amounts are expressed in billion euros of market value, and correspond to 2020 Q4 holdings. OFI (*Other Financial Institutions*) includes OFI (for instance, security and derivatives dealers), and FVC (*Financial Vehicles Corporations*). The sector *Other* includes government and non-financial corporations holdings. Securities are counted as eligible (resp. purchased) if they are eligible (resp. purchased) at least once over 2014 Q3-2020 Q4.

Table 3.10: Descriptive statistics AnaCredit

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 50	Pctl. 75	Max
CET1 Ratio (%)	613	16.32	5.48	6.63	13.4	14.99	17.17	50
LCR Ratio (%)	440	166.58	60.95	91	138	152	173.69	587
Total Asset Growth (%)	613	1.26	3.92	-9.7	-0.74	0.84	2.84	13.46
NFPS Deposit Growth (%TA)	394	1.46	3.72	-9.08	-0.32	0.96	2.74	15.4
CB Funding Growth (%TA)	394	0.55	2.22	-5.68	0	0	0.65	7.41
Total Asset (bn)	623	317.19	487.47	2.6	47.81	86.23	297.9	2715.15
Sales (%)	634	0.22	0.39	0	0	0.06	0.25	3.78
Share Eligible (%)	616	12.46	8.69	0	5.35	11.62	19.21	39.23
Total loans (bn)	688	14.47	22.02	0	1.25	5.68	15.9	117.51
No. Loans (#)	9	1.33	1	1	1	1	1	4

Table 3.11: Descriptive statistics banks

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 50	Pctl. 75	Max
CET1 Ratio (%)	1336	16	6.7	6.6	13	14	17	50
LCR Ratio (%)	876	163	75	2.5	128	145	169	603
Total Asset Growth (%)	1258	0.76	3.5	-9.6	-0.84	0.48	2.2	13
NFPS Deposit Growth (%TA)	864	0.77	3.2	-9.1	-0.77	0.55	2	13
Central Bank Funding Growth (%TA)	865	0.34	1.6	-4.9	0	0	0.061	7.4
Total Asset (bn)	1361	408	524	2.6	57	170	599	2715
Sales (%)	1370	0.22	0.38	0	0.00059	0.073	0.27	3.8
Share Eligible (%)	1353	11	7.5	0	5.1	9.7	15	39
Total bonds (bn)	1378	57	66	0.021	9.4	29	77	342
No. bonds (#)	1378	3865	9062	2	232	677	2442	61740
Total shares (bn)	1102	9.5	18	0	0.042	0.44	9.2	89
No. shares (#)	1102	1058	2566	0	10	71	350	14690
Total fund shares (bn)	1167	1.9	3.5	0	0.029	0.29	1.7	23
No. fund shares (#)	1167	297	643	0	8	40	166	4754

Table 3.12: Descriptive statistics funds

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 50	Pctl. 75	Max
Cash Ratio (%)	57141	3.7	6.9	0	0.17	1.2	4.6	95
Total Asset Growth (%)	54407	1.6	15	-40	-3.3	0.32	3.9	88
Total Asset (bn)	57183	0.27	1.1	0.00017	0.027	0.082	0.22	57
Sales (%)	55417	0.75	3	0	0	0	0	99
Share Eligible (%)	49343	26	25	0	4.7	19	40	100
Total bonds (bn)	51031	0.18	0.91	0	0.0074	0.04	0.13	114
No. bonds (#)	51031	55	70	0	16	38	73	2252
Total shares (bn)	19008	0.081	0.37	0	0.0025	0.012	0.053	12
No. shares (#)	19008	48	71	0	18	37	55	1520
Total fund shares (bn)	47221	0.039	0.13	0	0.002	0.0065	0.024	3.7
No. fund shares (#)	47221	5.8	7.3	0	1	3	8	97

Table 3.13: Descriptive statistics icpf

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 50	Pctl. 75	Max
SCR Ratio (%)	593	2.2	0.69	1.1	1.7	2	2.4	5.2
Cash Ratio (%)	592	3.3	3.6	-1.2	0.69	2.4	4.5	24
Total Asset Growth (%)	549	0.96	3.2	-7.5	-0.44	0.65	2.1	13
Total Asset (bn)	593	84	148	0.22	4.1	21	107	709
Sales (%)	604	0.28	1.9	0	0	0.011	0.12	39
Share Eligible (%)	584	23	13	0.0000002	14	23	31	97
Total bonds (bn)	611	49	95	0	1.2	7.6	64	695
No. bonds (#)	611	1437	1909	0	435	817	1804	12392
Total shares (bn)	567	4	6.5	0	0.07	0.29	6	27
No. shares (#)	567	328	561	0	18	75	392	2879
Total fund shares (bn)	612	18	31	0.00075	0.52	4.3	21	117
No. fund shares (#)	612	1313	2291	6	48	170	1594	12252

C. Additional tables

Table 3.14: Sensitivity of sectors to Eurosystem purchases relative to banks

	Dependent variable:			
	All	Covered	Government	Corporate
	(1)	(2)	(3)	(4)
QE	-1.022***	-1.466***	-0.916***	-1.333***
	(0.104)	(0.195)	(0.097)	(0.207)
QE:ICPF	0.830***	0.902***	0.674***	1.085***
	(0.182)	(0.255)	(0.178)	(0.267)
QE:FUND	0.414***	0.919***	0.474***	0.049
	(0.153)	(0.205)	(0.159)	(0.281)
$\Delta FaceValue$	0.626***	0.375***	0.844***	0.640***
	(0.030)	(0.042)	(0.038)	(0.052)
$\Delta Rating$	-0.030***	-0.052***	0.002	-0.003
	(0.007)	(0.010)	(0.010)	(0.006)
Sector x Quarter FE	Yes	Yes	Yes	Yes
ISIN FE	Yes	Yes	Yes	Yes
Observations	361,265	125,131	127,080	127,806
R^2	0.113	0.105	0.106	0.149

Notes: Covered corresponds to bank covered bonds purchased in CBPP3, *Government* to government bonds purchased in PSPP, and *Corporate* to corporate bonds purchased in CSPP. PEPP purchases are reallocated to the three asset categories according to the type of asset purchased. All variables are expressed in mid-point growth rates in points (1=100%), except for the variation in PD which increases by 1 for each drop of rating letter bucket (using S&P standard scale). Standard errors are clustered at the sector-quarter and ISIN level. *p<0.1; **p<0.05; ***p<0.01.

Table 3.15: Sensitivity of sectors to Eurosystem purchases relative to funds

	Dependent variable:			
	All	Covered	Government	Corporate
	(1)	(2)	(3)	(4)
QE	-0.608***	-0.548***	-0.442***	-1.284***
	(0.095)	(0.150)	(0.132)	(0.159)
QE:ICPF	0.416**	-0.017	0.200	1.036***
	(0.159)	(0.233)	(0.179)	(0.184)
QE:BANK	-0.414***	-0.919***	-0.474***	-0.049
	(0.153)	(0.205)	(0.159)	(0.281)
$\Delta FaceValue$	0.626***	0.375***	0.844***	0.640***
	(0.030)	(0.042)	(0.038)	(0.052)
$\Delta Rating$	-0.030***	-0.052***	0.002	-0.003
	(0.007)	(0.010)	(0.010)	(0.006)
Sector x Quarter FE	Yes	Yes	Yes	Yes
ISIN FE	Yes	Yes	Yes	Yes
Observations	361,265	125,131	127,080	127,806
R^2	0.113	0.105	0.106	0.149

Notes: *Covered* corresponds to bank covered bonds purchased in CBPP3, *Government* to government bonds purchased in PSPP, and *Corporate* to corporate bonds purchased in CSPP. PEPP purchases are reallocated to the three asset categories according to the type of asset purchased. All variables are expressed in mid-point growth rates in points (1=100%), except for the variation in PD which increases by 1 for each drop of rating letter bucket (using S&P standard scale). Standard errors are clustered at the sector-quarter and ISIN level. *p<0.1; **p<0.05; ***p<0.01.

Table 3.16: First stage - effect of asset sales on securities growth, ICPF

	Asset Sales						
	Debt	Shares	Fund shares	EA Debt	Non-EA Debt	IG Debt	HY Debt
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share eligible Lag	0.014	0.014	0.035*	0.015	0.016*	0.015	0.007*
	(0.009)	(0.010)	(0.018)	(0.010)	(0.009)	(0.010)	(0.004)
Total Assets Growth Lag	−0.016	−0.016	0.003	−0.021	−0.005	−0.015	0.005
	(0.014)	(0.020)	(0.015)	(0.016)	(0.011)	(0.014)	(0.004)
Total Assets Lag	−0.019	−0.038	−0.126	0.006	−0.051*	−0.018	−0.015
	(0.019)	(0.025)	(0.089)	(0.021)	(0.027)	(0.019)	(0.020)
SCR Ratio Lag	−0.170	−0.140	−0.233**	−0.213	−0.114	−0.187	−0.032
	(0.125)	(0.126)	(0.115)	(0.157)	(0.082)	(0.136)	(0.039)
Cash Ratio Lag	0.009	0.009	−0.016	0.026	−0.001	0.010	−0.007
	(0.019)	(0.023)	(0.025)	(0.025)	(0.018)	(0.020)	(0.009)
Asset Sales Lag	0.001	0.003	−0.003	0.002	0.001	0.009	−0.0004
	(0.011)	(0.008)	(0.007)	(0.016)	(0.006)	(0.010)	(0.001)
ISIN x Quarter FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	340,426	189,299	795,472	136,557	203,869	267,398	22,279
R^2	0.898	0.696	0.755	0.755	0.946	0.899	0.616

Notes: Standard errors are clustered at the investor-quarter and ISIN level. *Asset sales* are expressed in points of banks lagged total assets (1 = 100%). *Share eligible lag* is expressed in points (1 = 100%) and right-winsorized at 2.5%. All growth rates and ratios are expressed in points of lagged total assets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 3.17: First stage - effect of asset sales on securities growth, banks

	Asset Sales						
	Debt	Shares	Fund shares	EA Debt	Non-EA Debt	IG Debt	HY Debt
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share eligible Lag	0.023***	0.027***	0.028***	0.027***	0.019***	0.022***	0.041***
	(0.003)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.006)
Total Assets Growth Lag	0.011*	0.007**	0.011***	0.015**	0.007	0.012*	0.014**
	(0.006)	(0.003)	(0.004)	(0.007)	(0.006)	(0.007)	(0.006)
Total Assets Lag	0.089***	0.104***	0.097***	0.093***	0.085***	0.088***	0.176***
	(0.014)	(0.026)	(0.027)	(0.016)	(0.014)	(0.014)	(0.031)
CET1 Ratio Lag	-0.002	-0.005	-0.001	-0.001	-0.002	-0.002	0.020**
	(0.003)	(0.006)	(0.007)	(0.003)	(0.003)	(0.003)	(0.008)
LCR Ratio Lag	-0.001**	-0.001	-0.001	-0.001***	0.0002	-0.001	-0.002***
	(0.0004)	(0.001)	(0.001)	(0.0005)	(0.0005)	(0.0004)	(0.001)
NFPS Deposit Growth Lag	-0.001	0.009	0.010*	-0.002	0.001	-0.004	-0.002
	(0.004)	(0.006)	(0.006)	(0.005)	(0.004)	(0.005)	(0.006)
Central Bank Funding Growth	1.079	-0.222	-0.056	0.761	1.379*	0.948	2.445*
	(0.732)	(0.691)	(0.588)	(0.752)	(0.788)	(0.791)	(1.308)
Asset Sales Lag	0.464***	0.267***	0.307***	0.400***	0.567***	0.437***	0.303***
	(0.057)	(0.098)	(0.097)	(0.058)	(0.073)	(0.058)	(0.092)
ISIN x Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	951,410	902,757	246,033	519,950	431,460	442,262	51,210
R^2	0.942	0.822	0.940	0.957	0.860	0.934	0.919

Notes: Standard errors are clustered at the investor-quarter and ISIN level. *Asset sales* are expressed in points of banks lagged total assets (1 = 100%). *Share eligible lag* is expressed in points (1 = 100%) and right-winsorized at 2.5%. All growth rates and ratios are expressed in points of lagged total assets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 3.18: First stage - effect of asset sales on securities growth, funds

	Asset Sales						
	Debt	Shares	Fund shares	EA Debt	Non-EA Debt	IG Debt	HY Debt
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share eligible Lag: Debt funds	0.0257***	0.0353***	0.0319***	0.0252***	0.0268***	0.0252***	0.0204***
	(0.0013)	(0.0066)	(0.0043)	(0.0016)	(0.0016)	(0.0015)	(0.0021)
Share eligible Lag: Diversified funds	0.0202***	0.0232***	0.0248***	0.0184***	0.0251***	0.0190***	0.0221***
	(0.0043)	(0.0070)	(0.0038)	(0.0054)	(0.0049)	(0.0050)	(0.0074)
Share eligible Lag: Other funds	0.0226***	0.0536**	0.0326***	0.0209**	0.0308***	0.0203**	0.0208
	(0.0085)	(0.0263)	(0.0061)	(0.0106)	(0.0106)	(0.0098)	(0.0190)
ISIN x Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	934,735	808,537	243,502	567,847	812,084	661,603	110,538
R^2	0.217	0.213	0.378	0.170	0.342	0.134	0.151

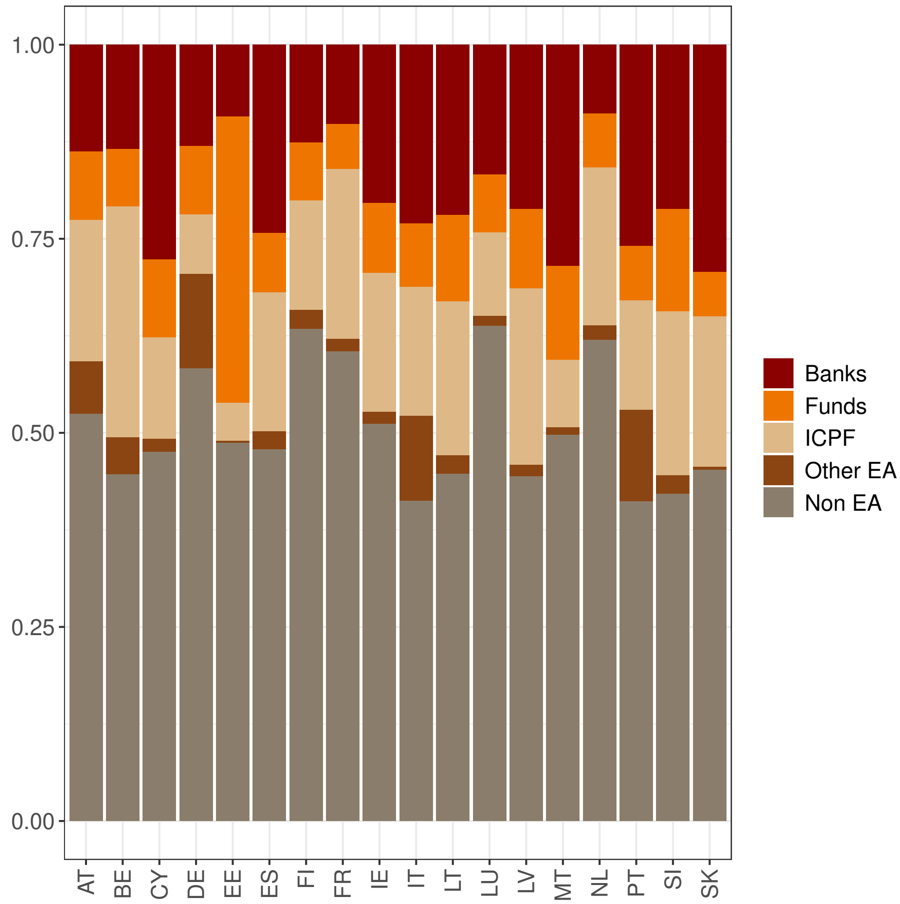
Notes: Standard errors are clustered at the investor-quarter and ISIN level. *Asset sales* are expressed in points of banks lagged total assets (1 = 100%). *Share eligible lag* is expressed in points (1 = 100%) and right-winsorized at 2.5%. All growth rates and ratios are expressed in points of lagged total assets. Growth rates are all winsorized at 1% on both sides. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 3.19: First stage - effect of asset sales on loan growth

	Asset Sales		
	2-stage WLS (1)	2SLS (2)	ValGains (3)
Share eligible lag	2.842***	2.994***	2.830***
	(0.758)	(0.765)	(0.776)
Asset Sales Lag	0.400***	0.389***	0.400***
	(0.152)	(0.135)	(0.152)
Total Assets Lag	0.060*	0.052	0.060*
	(0.034)	(0.034)	(0.034)
Total Assets Growth Lag	0.032*	0.033*	0.032*
	(0.017)	(0.017)	(0.018)
CET1 Ratio Lag	0.008	0.001	0.008
	(0.006)	(0.007)	(0.006)
LCR Ratio Lag	-0.002**	-0.002**	-0.002**
	(0.001)	(0.001)	(0.001)
NFPS Deposit Growth Lag	-0.007	0.001	-0.007
	(0.011)	(0.010)	(0.011)
Central Bank Funding Growth	-0.001	-0.004	-0.001
	(0.013)	(0.013)	(0.013)
Valuation Gains			0.028
			(0.083)
Num.Obs.	6185245	6185245	6185245
Firm-quarter FE	Yes	Yes	Yes

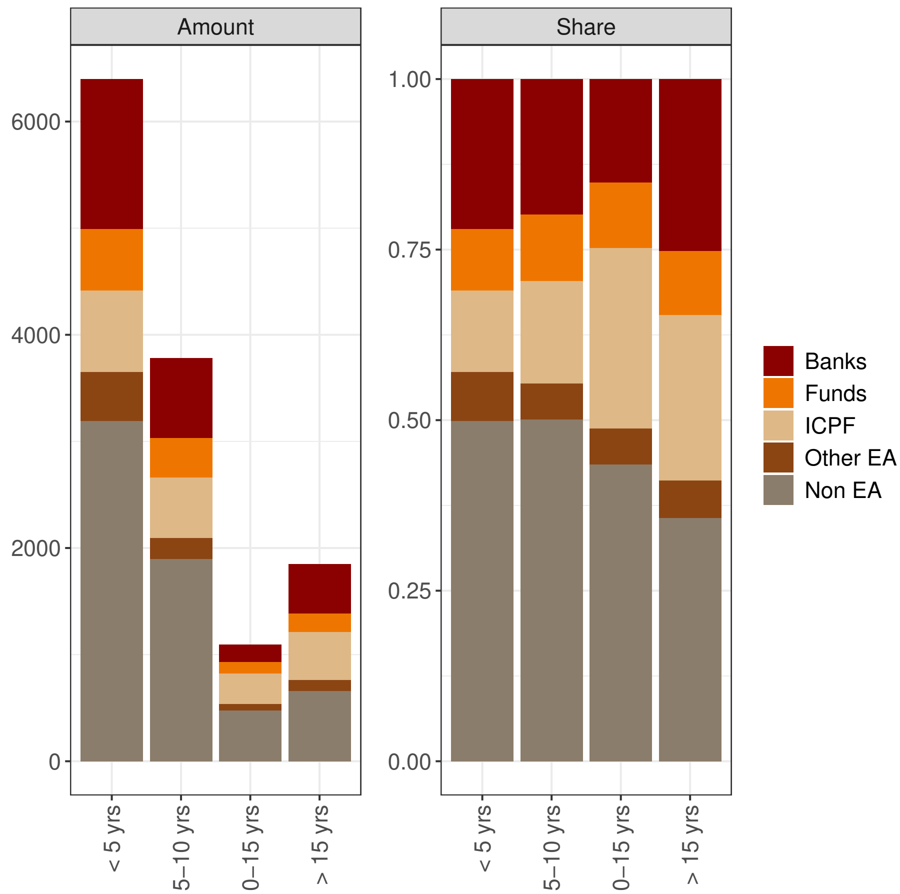
Notes: Standard errors are clustered at the bank-quarter and firm level. The lagged share of assets eligible on banks balance sheet *Share eligible lag* is expressed in points (1 = 100%). The dependent variable *Asset sales* is expressed in pp of bank lagged total assets. All growth rates and ratios are expressed in points of lagged total assets. *p<0.1; **p<0.05; ***p<0.01.

D. Additional figures



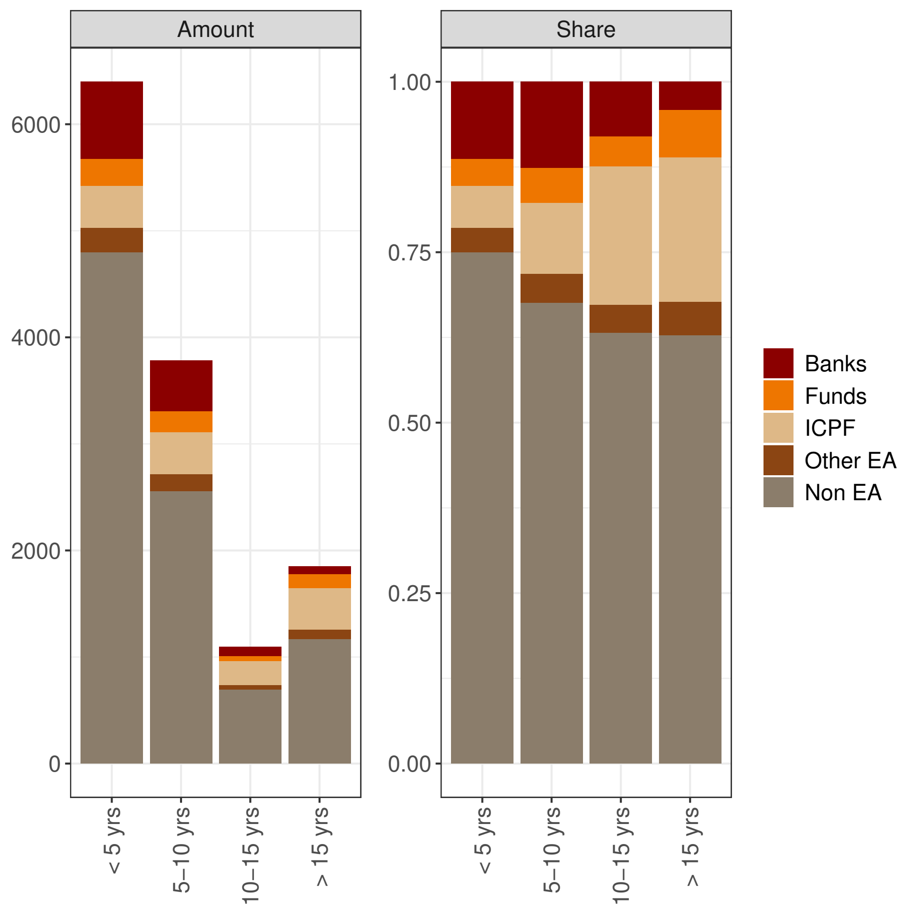
Notes: Share of face value ownership of PSPP-eligible securities, by sector and country of issuance.

Fig. 3.4. Holdings of PSPP-eligible securities per issuer country



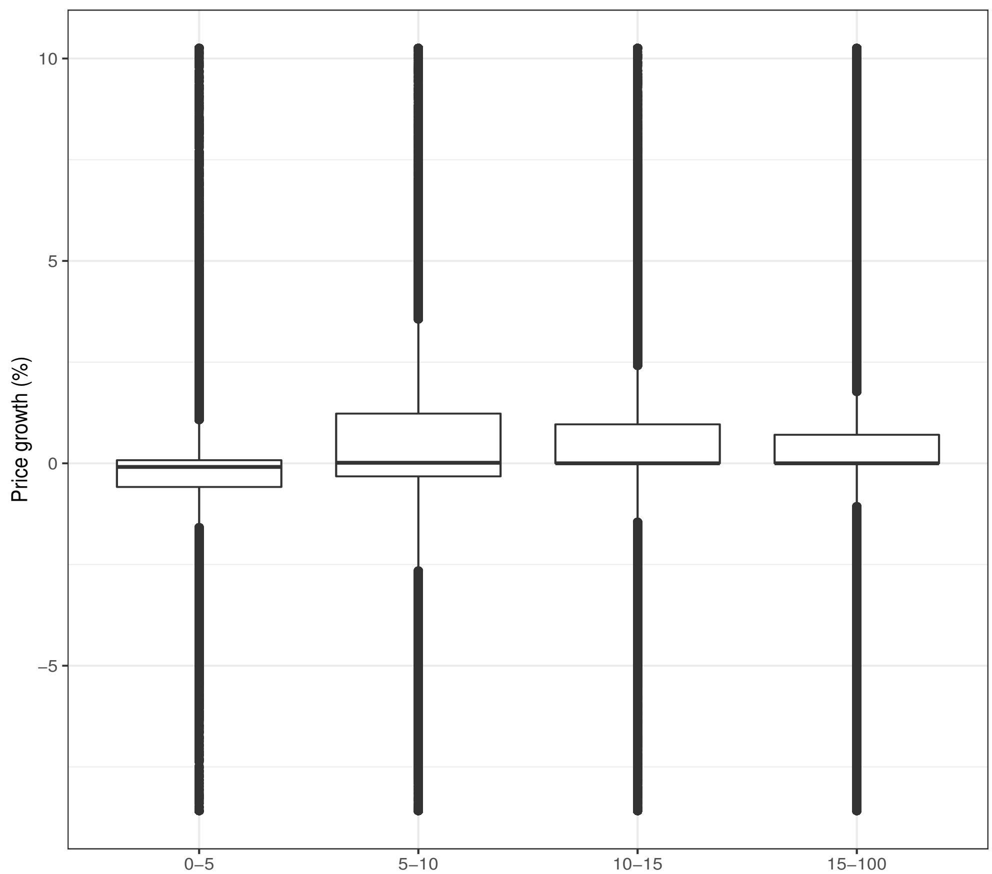
Notes: Face value of holdings by sector and residual maturity in billion euros (left hand side), and share of face value ownership by sector and residual maturity (right hand side).

Fig. 3.5. Holdings of debt securities by residual maturity as of end-2020



Notes: Face value of holdings by sector and residual maturity in billion euros (left hand side), and share of face value ownership by sector and residual maturity (right hand side).

Fig. 3.6. Holdings of debt securities by residual maturity for PSPP-eligible securities as of end-2020



Notes: Price growths are winsorized at 1% on both sides.

Fig. 3.7. Pooled distribution of quarterly price growth of securities eligible at least once to purchases

Conclusion

This PhD thesis is devoted to macroprudential and monetary policy, and to changes to the conduct of these policies that occurred in the wake of the Global Financial Crisis.

In Chapter 1, we exploit the institutional setup of the CCyB in the European Economic Area to directly estimate the effect of capital requirements on financial markets. Our identification rests upon two features: CCyB hikes are quarterly announcements by national authorities, and they heterogeneously affect all banks of the EEA. We use this setup to assess how markets factor capital requirement increases in CDS spreads and stock prices. We show that hikes in CCyB rates are perceived as increasing bank solvency, at no significant cost for shareholders. We claim that these effects relate to the capital constraint itself, as opposed to the potential signal conveyed on the state of the financial cycle. The impact on CDS spreads is materially larger for banks poorly capitalised, as they are more likely to adjust to higher requirements and their solvency should benefit more from an additional unit of capital. These results are important to assess the costs and benefits of capital requirements. Our results suggest that regulators were able to enhance bank solvency at no significant cost for shareholder. Looking ahead, regulators may be able to further increase CCyB rates without significantly affecting shareholder value.

In Chapter 2, we use quarterly granular data on both debt and CDS exposures to study how CDS reallocate credit risk across investors. CDS represent a limited share of aggregate credit risk exposures, but a large share of exposures to the reference entities on which CDS are traded. We propose a methodology to disentangle CDS positions into three strategies: speculators use CDS to amplify their original debt exposures or originate new ones; hedgers use them to reduce debt exposures after unexpected shocks or to maintain lending relationships; arbitrageurs make profit out of the CDS-bond basis, but represent an anecdotal share of strategies. CDS trading affects credit risk allocation in three manners. First, the introduction of CDS increases the amount of outstanding credit risk exposures, by 10 to 15% on the subsample of large NFCs which reference CDS. CDS also impact credit risk concentration, with hedgers using CDS to shed off their most concentrated exposures, while speculators complement their existing debt exposures by selling CDS. Finally, CDS facilitate

risk-taking for most sectors and trading strategies, thereby increasing the average riskiness of credit risk exposures. Overall, the consequences of credit risk redistribution for financial stability appear ambiguous since hedging the most concentrated and riskiest exposures potentially offsets the other effects identified. Measuring the contribution of CDS to systemic risk through higher granular risk in a normative framework is left for future research.

In Chapter 3, we show that central bank asset purchase programs do not have the same effect on portfolio rebalancing depending on the type of securities purchased. We show that who initially holds the securities purchased matters. First, we show that different types of purchases are accommodated by different types of investors. Among EA investors, sovereign debt securities and bank covered bonds are primarily sold by banks who are both the most elastic to purchases and the largest holders of such securities. IF are the largest sellers of corporate securities as they exhibit similar elasticities to banks, together with larger initial holdings. Across maturities, we find that investment funds tend to exhibit some preferred habitat behavior and are less elastic to purchases of securities closer to their maturity habitat, while there are signs that ICPF are reaching for maturity. In the second part of the paper, we show that different types of investors rebalance differently upon selling to the Eurosystem. Banks selling to the Eurosystem tend to increase lending. ICPF marginally increase their demand for non-euro area debt securities. Funds with flexible mandates tend to increase demand for all types of debt securities and equities, while less flexible funds tend to substitute the securities sold with similar securities. Our findings have important implications for the design of central bank asset purchase (and divestment) programs. Beyond the amount of risk that the central bank decides to bear, the structure of asset demand for the securities purchased will matter for monetary policy transmission and potential financial stability spillovers.

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Essais en Politique Macroprudentielle et Monétaire

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Résumé

Essais en Politique Macroprudentielle et Monétaire

La politique monétaire et la politique macroprudentielle sont sans doute les deux principales missions de nos jours communément attribuées aux banques centrales. En essence, la première vise à garantir la stabilité des prix à la *consommation*, tandis que la seconde se concentre sur la stabilité des prix des *actifs*. Aucun de ces objectifs de politique économique n'est nouveau. Cependant, tant la mise en pratique de ces politiques que les théories qui les sous-tendent ont connu une évolution considérable au cours des quinze dernières années, suite à l'éclatement de la crise financière mondiale de 2008. Cette thèse contribue à la compréhension des évolutions récentes dans ces deux domaines.

Les deux premiers chapitres de cette thèse contribuent à la littérature sur la politique macroprudentielle, par le biais d'une évaluation a posteriori d'un instrument macroprudentiel clé, le coussin de fonds propres contracyclique (Chapitre 1), et en examinant une source potentielle de risque systémique, l'échange de dérivés de crédit (en anglais *Credit Default Swaps*, ci-après CDS), qui redistribue le risque de crédit au sein du secteur financier (Chapitre 2). Le Chapitre 3 est ensuite consacré à la politique monétaire, à travers une évaluation des effets hétérogènes de l'assouplissement quantitatif en zone euro.

La crise de 2008 a rappelé dans la douleur que les crises financières peuvent encore survenir malgré une solide supervision microprudentielle. Une raison importante avancée notamment par Brunnermeier (2009) dans son compte-rendu détaillé de la crise est la procyclicité naturelle de la prise de risque découlant du "déclin des risques mesurés pendant toute période d'essor, suivi de la hausse de ces risques durant toute récession". Ce diagnostic a entraîné une révision importante de la réglementation financière. Bien que le concept de politique macroprudentielle ne soit pas nouveau,[1] les accords de Bâle III ont introduit officiellement plusieurs instruments explicitement dédiés à la gestion des risques systémiques. L'un des instruments phares fut le coussin de fonds propres contracyclique (en anglais *countercyclical capital buffer*, ci-après CCyB), visant à accroître la résilience du secteur bancaire en obligeant les banques à accumuler du capital pendant les périodes de croissance soutenue du crédit. Inversement, cette exigence est assouplie lors des retournements de conjoncture, afin de soutenir la distribution du crédit par les banques en leur fournissant une marge de manœuvre en capital. Plusieurs études ont récemment utilisé les assouplissements des exigences en capital durant la crise du COVID-19 pour démontrer leur effet sur l'offre de crédit (Couaillier et al., 2022; Martinez-Miera and Vegas Sánchez, 2021).

Le premier chapitre de cette thèse s'intéresse à l'utilisation du CCyB en Europe de 2016

[1] L'utilisation du terme "macroprudentiel" remonte généralement au rapport Cross de 1986 de la Banque des règlements internationaux.

à début 2022, afin de comprendre comment les marchés réagissent aux exigences en capital en général, et aux exigences en capital cyclique en particulier. Le cadre européen du CCyB offre une configuration idéale à cet égard. Tout d'abord, les autorités nationales fixent les exigences de CCyB dans toutes les juridictions à une fréquence prédéfinie (trimestrielle), ce qui fournit un ensemble conséquent d'annonces comparables. Deuxièmement, le taux du CCyB dans un pays donné s'applique à toutes les banques de l'Espace économique européen (EEE) proportionnellement à la part de ce pays dans leurs expositions totales (pertinentes). Par conséquent, chaque choc affecte de manière hétérogène l'ensemble des banques de l'EEE, permettant ainsi des analyses transversales. Nous démontrons que les hausses du CCyB se traduisent par une réduction des primes de CDS pour les banques concernées, en particulier celles qui sont les moins capitalisées. En revanche, les valorisations bancaires ne réagissent pas. Les marchés considèrent donc que ces exigences rendent les banques plus stables à coût nul pour les actionnaires. Nous soutenons que ces effets sont liés à la contrainte de capital elle-même, plutôt qu'au signal transmis sur l'état du cycle financier par le régulateur. En effet, les mesures de risque et de rendement à l'échelle du marché, telles que les primes de CDS souverains et les indices boursiers, ne réagissent pas davantage à ces annonces. À notre connaissance, cette étude est la première à fournir une évaluation directe de la manière dont les marchés valorisent les exigences en capital. En fin de compte, nos conclusions suggèrent que les autorités macroprudentielles pourraient utiliser de manière plus active le CCyB, ce qui semble en effet être la tendance plus récente.

Les risques systémiques émergent souvent dans un contexte d'innovations financières. Le développement généralisé du marché des CDS dans la période précédant la crise de 2008 en est un exemple. Entre 2004 et 2008, la taille du marché des CDS, en termes de notionnel, est passée de 6 billions de dollars à un pic de 57 billions de dollars (Stulz, 2010). Ces instruments permettent de séparer le risque de financement du risque de crédit, et potentiellement de réallouer ces risques aux bilans les mieux à même de les supporter (Oehmke and Zawadowski, 2015). En pratique, les CDS ont été utilisés pour *concentrer* le risque de crédit sur des bilans apparemment sûrs, tels que celui de l'assureur AIG, qui pouvait le supporter à un coût réglementaire limité, ce qui apparaît rétrospectivement comme une forme d'arbitrage réglementaire (voir McDonald and Paulson (2015) pour une analyse détaillée de la faillite d'AIG). Limiter la concentration des expositions est ainsi devenu un objectif explicite de la politique macroprudentielle.[2]

Au Chapitre 2, nous utilisons un nouvel ensemble de données de détentions de CDS par les investisseurs français, ou portant sur des sous-jacents français, afin de comprendre les

[2]Voir ESRB (2013).

déterminants actuels des échanges de CDS et leurs conséquences sur la répartition du risque de crédit. En effet, et malgré les événements de la crise financière, les effets distributifs des échanges de CDS sont encore mal compris, pour au moins deux raisons. Premièrement, les CDS sont un jeu à somme nulle en économie fermée, et les paiements qui en résultent ne sont que des transferts à l'intérieur du système financier. Cependant, des contributions récentes telles que Gabaix (2011), Galaasen et al. (2020) ou Baena et al. (2022) soulignent comment les difficultés d'un investisseur individuel peuvent affecter l'offre de crédit et l'activité économique. Ainsi, les expositions individuelles au risque de crédit peuvent avoir une incidence sur la stabilité financière. Deuxièmement, l'étude du risque de crédit au niveau individuel requiert des données granulaires sur plusieurs instruments (crédits, obligations, CDS), qui sont difficiles à obtenir et à traiter, et auxquelles les chercheurs n'ont commencé à s'intéresser que récemment. En Europe, les régulateurs n'ont accès à des données granulaires sur les détentions et les transactions de CDS que depuis 2016, grâce au Règlement européen sur les infrastructures de marché (en anglais *European Markets Infrastructure Regulation*, ci-après EMIR) de 2012.[3] Dans cet article, nous analysons conjointement les trois types d'expositions et montrons que si les CDS représentent une faible part du risque de crédit agrégé, cette part devient élevée envers les plus grands emprunteurs. Nous proposons une méthodologie pour distinguer les positions en CDS en fonction de trois stratégies : la couverture, la spéculation et l'arbitrage. Chacune de ces stratégies a des conséquences différentes sur la redistribution du risque de crédit. Premièrement, étant donné que la majorité des CDS achetés ne neutralisent pas des expositions en dette pré-existantes, leur échange entraîne une augmentation agrégée des expositions au défaut. Deuxièmement, nous constatons que les stratégies de couverture et de spéculation sont liées à la concentration des expositions correspondantes en dette. En utilisant un nouvel instrument pour la concentration de la dette, nous montrons que les banques qui se couvrent ont tendance à se délester de leurs expositions les plus concentrées, tandis que les spéculateurs vendent les CDS en complément de l'achat de dette. Enfin, nous démontrons que les incitations des investisseurs à échanger des CDS augmentent avec le risque du sous-jacent, modifiant ainsi la composition de l'encours de risque de crédit. Dans l'ensemble, nos résultats soulignent l'importance de prendre en compte les CDS lors de l'analyse de la distribution des grandes expositions au risque de crédit entre investisseurs.

Sur le front de la politique monétaire, le risque de déflation ayant émergé dans le sillage de la crise financière a entraîné d'importantes interventions des banques centrales à travers le

[3]Règlement (UE) n° 648/2012 du 4 juillet 2012 sur les dérivés de gré à gré, les contreparties centrales et les référentiels centraux.

monde - avec la mise en place des politiques monétaires dites non conventionnelles. Quinze ans plus tard, ces politiques font désormais partie de l'arsenal des banques centrales. Dans le cadre de sa revue stratégique, et tout en reconnaissant que les taux directeurs restaient l'instrument principal, la Banque centrale européenne (BCE) a admis qu'elle continuerait à utiliser des instruments non conventionnels tels que le guidage des anticipations, les achats d'actifs et les opérations de refinancement à plus long terme, en cas de besoin.[4] Dans les économies où les taux d'intérêt à court terme peuvent occasionnellement devenir si bas que les banques centrales ne peuvent plus les baisser, ces politiques permettent aux banques centrales de continuer à stabiliser l'économie en pilotant les taux d'intérêt à plus long terme via divers canaux. Les programmes d'achat d'actifs sont en général considérées comme les plus notables de ces politiques. Schématiquement, les achats d'actifs opèrent en transférant du risque de duration, de liquidité et de crédit au bilan de la banque centrale, augmentant ainsi la capacité des agents privés à porter des risques. Ces derniers sont incités à *rééquilibrer* leur portefeuille vers des actifs alternatifs : c'est le canal de rééquilibrage du portefeuille de l'assouplissement quantitatif (Vayanos and Vila, 2021).

Le dernier chapitre de cette thèse analyse comment différents types d'achats stimulent la demande pour différents types d'actifs en fonction de la structure de détention des titres achetés. Nous exploitons pour cela la diversité des programmes d'achats menés par l'Eurosystème de 2014 à 2020, afin de d'identifier les contreparties aux différents programmes d'achats. Nous constatons que parmi les investisseurs de la zone euro, les titres souverains et les obligations sécurisées bancaires sont principalement acquises auprès des banques, tandis que les titres des sociétés non-financières sont plutôt achetés à des fonds d'investissement. Nous montrons également que les choix de rééquilibrage de portefeuille des investisseurs dépendent de leur *habitat* d'investissement. L'achat de titres auprès des banques stimulera le crédit bancaire, tandis que les fonds d'investissement ont tendance à augmententer leur demande de titres plus risqués s'ils disposent du mandat requis. Concrètement, cela signifie que les banques centrales doivent non seulement définir la *quantité* de risque à acquérir, mais aussi identifier la nature des contreparties potentielles. Cela implique également qu'un programme d'achat d'actifs mené dans une union monétaire composée de pays aux structures financières diverses, comme la zone euro, peut avoir des effets hétérogènes entre pays. De manière symétrique, on peut s'attendre à ce que le resserrement quantitatif en cours comprime la demande de manière hétérogène à travers les géographies et les segments de marché, selon les choix de titres non renouvelés ou cédés effectués.

[4] Voir `https://www.ecb.europa.eu/home/search/review/html/ecb.strategyreview_monpol_strategy_statement.en.html`.

Je présente maintenant de manière plus détaillée les chapitres qui composent cette thèse de doctorat.

Chapitre 1 : Comment les marchés réagissent-ils au renforcement des exigences de fonds propres bancaires ?

La crise financière de 2008 a rappelé l'importance d'avoir un secteur bancaire suffisamment capitalisé, car les crises bancaires et les restrictions de crédit associées ont des conséquences importantes sur l'économie réelle. La principale réponse réglementaire à la crise a ainsi consisté en une augmentation importante des exigences en matière de capital bancaire. Cependant, leur niveau optimal fait l'objet d'un débat continu parmi les universitaires et les décideurs. Bien que des exigences plus élevées soient associées à une plus grande résilience, elles peuvent également inutilement contraindre le crédit (voir par exemple Van den Heuvel (2008), Repullo and Suarez (2012), Clerc et al. (2015), Mendicino et al. (2018), Malherbe (2020)). Il est donc essentiel pour les régulateurs de trouver le bon équilibre entre les avantages d'un système bancaire plus stable, et les pertes associées à une hausse du coût du capital. Dans cette étude, nous utilisons le cadre institutionnel du coussin de fonds propres contracyclique (CCyB) dans l'Espace économique européen (EEE) pour évaluer comment les marchés financiers perçoivent les coûts et bénéfices de l'augmentation des exigences en capital.

Le CCyB est une exigence en capital bancaire variable dans le temps, introduite dans les accords de de Bâle III, et désormais intégrée à la réglementation européenne. Ce coussin présente deux caractéristiques intéressantes une telle étude. Tout d'abord, les niveaux de CCyB sont des décisions homogènes annoncées trimestriellement dans chaque pays, et nous pouvons identifier précisément les dates d'annonce grâce aux communiqués de presse associés. Cela permet d'étudier l'effet du CCyB dans le cadre d'une approche dite événementielle. Deuxièmement, le taux du CCyB dans un pays donné s'applique à toutes les banques de l'EEE proportionnellement à la part de ce pays dans leurs expositions totales (pertinentes). Par conséquent, chaque choc affecte de manière hétérogène toutes les banques de l'EEE, ce qui permet des études transversales. A l'inverse, les changements d'exigences en capital faisaient traditionnellement suite à des réformes longuement négociées, et donc largement anticipées, ce qui ne permettait pas de mesurer d'effet sur les marchés. Ces réformes étaient en outre des événements ponctuels et associant de nombreuses dispositions, ce qui compliquait l'identification spécifique des effets des exigences en capital. En général, ces réformes s'appliquaient enfin à toutes les banques de la même manière, ce qui ne permettait pas

d'utiliser les différences d'effets entre banques comme technique d'identification. Avec Bâle III, d'autres exigences en capital affectant chaque banque de manière spécifique ont bien été introduites, mais leur calcul est souvent mécanique (comme par exemple pour les banques systémiques) et donc facilement anticipé, et/ou sans cadre de communication exploitable.[5]

Les augmentations de CCyB peuvent entrainer des réactions sur les marchés par le truchement de deux canaux. Tout d'abord, elles révèlent le diagnostic que le régulateur porte sur l'état de l'économie en fixant le taux, et en transparence les informations privées qu'il pourrait détenir. L'interprétation d'un tel signal est a priori ambiguë. Les autorités macroprudentielles augmentent généralement le CCyB lorsque l'économie est en bonne santé, mais aussi lorsque les risques financiers s'accumulent. Nous qualifions cela de *canal du signal*. Le deuxième canal concerne l'exigence elle-même, qui resserre la contrainte en capital, contraignant potentiellement les banques à ajuster leur bilan. Nous qualifions cela de *canal du capital*. Dissocier ces deux canaux est essentiel pour interpréter correctement les résultats en termes de coûts et bénéfices.

Nous procédons en trois étapes. Tout d'abord, nous étudions l'impact des hausses du CCyB sur les indicateurs de marché au niveau pays, à savoir les indices boursiers et les CDS souverains. Nous constatons l'absence d'impact significatif : les variables pays ne réagissent pas systématiquement aux augmentations du CCyB. Cela est incompatible avec le canal du signal, et suggère que tout impact passe par le canal du capital.

Deuxièmement, nous montrons que l'annonce d'une augmentation du CCyB dans un pays se traduit par une baisse des primes de CDS pour les banques exposées à ce pays. Les marchés reconnaissent donc que les exigences en capital améliorent la solvabilité des banques, ce qui est conforme aux études mettant en évidence leur effet sur les ratios de capital (Alfon et al., 2005) et la prise de risque (Behncke, 2022). L'effet est plus marqué pour les banques ayant des ratios de capital plus faibles et une distance plus faible à leur exigence réglementaire. L'interprétation est double. Les marchés anticipent que les banques plus contraintes sont davantage susceptibles d'ajuster leur bilan en faveur de ratios de capital plus élevés, et des ratios de capital plus élevés ont des effets plus importants sur la solvabilité des banques moins capitalisées.

Enfin, nous montrons que les augmentations de CCyB ne sont associées à aucune évolution particulière des cours boursiers des banques affectées. Cette absence d'effets, conjuguée à la baisse des primes de CDS, est à nouveau incompatible avec le canal du signal : de bonnes nouvelles économiques réduisant les primes de CDS devraient également augmenter la valeur

[5] Dans l'Union bancaire européenne, les recommandations au titre du pilier 2 sont confidentielles, et le Mécanisme de supervision unique ne publie les exigences au titre du pilier 2 s'appliquant aux établissements significatifs que depuis 2020. Voir `https://www.bankingsupervision.europa.eu/banking/srep/html/p2r.en.html`.

des actions. Cela confirme l'activation du canal du capital, mais d'une manière qui n'a pas d'impact significatif sur les valorisations boursières. Des cours boursiers élevés peuvent être bénéfiques pour un régulateur, s'ils suggèrent que le crédit n'est pas inutilement contraint, et s'ils renforcent la capacité des banques nationales à mobiliser des capitaux propres ou à résister à des prises de contrôle étrangères malvenues. Par conséquent, nous interprétons l'absence de réaction boursière comme une preuve que les effets potentiellement négatifs des hausses de CCyB sont limités.

Nous montrons également que les baisses de CCyB décidées pendant le COVID-19 ont eu un effet positif sur les primes de CDS bancaires et souverains, et ont été associées à une baisse des rendements des actions. Bien que ces résultats doivent être interprétés avec prudence, la plupart des baisses ayant eu lieu en mars 2020, une période hautement volatile associée à l'apparition de la pandémie, ils suggèrent qu'un canal du signal est bien à l'œuvre lors des relâchements du CCyB. Les marchés interprètent les relâchements comme un signe que les perspectives économiques se dégradent. Les périodes de relâchement sont typiquement des périodes de plus forte volatilité où le diagnostic du régulateur éclaire davantage les marchés.

Nos résultats suggèrent donc que les autorités macroprudentielles ont la possibilité d'utiliser de manière plus active le CCyB pour accroître la résilience des banques, étant donné que les hausses que nous observons n'ont pas généré de réaction boursière significative.

Chapitre 2 : Stratégies d'échange de CDS et réallocation du risque de crédit

Les produits dérivés de crédit (CDS) sont des instruments financiers controversés, qualifiés "d'armes de destruction massive" par W. Buffet. D'un côté, les CDS peuvent améliorer l'allocation du risque en permettant aux investisseurs peu liquides mais optimistes de prendre une exposition au risque de crédit (Oehmke and Zawadowski, 2015). D'un autre côté, les CDS réduisent les incitations au suivi des emprunteurs en raison du problème dit du créancier vide (Bolton and Oehmke, 2011), et peuvent même faciliter la coordination des agents vers de "mauvais" équilibres (Bruneau et al., 2014). Ces travaux se concentrent principalement sur la manière dont les CDS influencent les prix des actifs ou le risque crédit des sous-jacents. Cependant, ils restent muets face aux effets des CDS sur la distribution du risque de crédit parmi les investisseurs, pour au moins deux raisons.

Premièrement, les CDS sont un jeu à somme nulle en économie fermée, et les paiements auxquels ils donnent lieu ne sont que des transferts au sein du système financier. Cependant, des contributions récentes telles que celles de Gabaix (2011), Galaasen et al. (2020) ou Baena

et al. (2022) soulignent comment des chocs affectant des investisseurs isolément peuvent tout de même affecter l'offre de crédit et l'activité économique. Les expositions individuelles au risque de crédit peuvent donc avoir une importance pour la stabilité financière.[6] Deuxièmement, l'étude des effets redistributifs des CDS requiert des données granulaires sur plusieurs instruments (crédits, obligations et CDS), qui sont difficiles à obtenir et traiter, et qui n'ont attiré l'attention des chercheurs que récemment.

En utilisant des données granulaires trimestrielles sur les expositions à la dette et aux CDS des investisseurs français envers les sociétés non financières (SNF), et des banques et fonds d'investissement de la zone euro envers les SNF françaises, de 2016T1 à 2021T4, nous apportons une nouvelle perspective sur la manière dont les CDS réallouent le risque de crédit entre investisseurs. Cela se produit de trois manières.

Premièrement, les échanges de CDS peuvent augmenter le montant *total* des expositions des investisseurs au défaut (EAD), dans la mesure où tous les achats de CDS ne compensent pas des expositions à la dette préexistantes.[7] Deuxièmement, les échanges de CDS peuvent modifier la *concentration* des expositions parmi les investisseurs. Enfin, les CDS peuvent également altérer la *composition* de l'encours de risque de crédit.

Notre première contribution est de proposer une méthodologie permettant d'identifier les stratégies sous-jacentes aux détentions de CDS. Nous distinguons trois stratégies, chacune ayant des conséquences différentes sur l'allocation du risque de crédit : l'arbitrage, la couverture et la spéculation. Pour ce faire, nous examinons tout d'abord si les expositions à la dette et aux CDS se compensent ou s'amplifient, si la dette est sous forme d'obligations ou de prêts, et si les positions sont acquises simultanément ou successivement.

Les arbitrageurs prennent des positions se neutralisant dans les deux marchés afin de tirer profit d'écarts de prix éventuels. Nous les identifions comme des positions de sens opposé, lorsque la dette ne prend que la forme d'obligations, et lorsque les positions sont acquises simultanément. Cette stratégie est anecdotique et représente 2% des acheteurs de CDS, et seulement 0,03% des vendeurs de CDS.

Les investisseurs utilisant les CDS à des fins de couverture le font soit en réaction à

[6] L'étude du risque de crédit au niveau individuel est égalemet pertinente vu la réglementation des fonds propres bancaires, qui limite l'utilisation des CDS à des fins de couverture aux instruments de dette portant sur la même entité de référence. L'article 213 du Règlement sur les exigences de fonds propres (CRR) de l'Union européenne stipule que “la protection du crédit provenant d'une garantie ou d'un dérivé de crédit doit être considérée comme une protection de crédit non financée éligible lorsque toutes les conditions suivantes sont remplies : (a) la protection de crédit est directe [...]”.

[7] Le concept prudentiel d'exposition au défaut correspond aux pertes potentielles de chaque investisseur en cas de défaut de l'emprunteur. Dans le cas d'échanges de CDS, l'augmentation de l'exposition au défaut du vendeur fait miroir à une baisse d'exposition au défaut de l'acheteur s'il neutralise une partie de ses détentions de dette, mais peut aussi faire miroir à un gain pour un autre investisseur auquel cas la somme des expositions au défaut individuelles augmente.

des chocs, soit pour maintenir des relations commerciales avec leurs clients dans le cas des banques.[8] Nous les identifions comme des positions de sens opposé, lorsque le CDS est acheté après la dette, ou lorsque les deux sont acquis conjointement et que la dette est au moins partiellement un crédit. La couverture représente 19% des achats de CDS et correspond presque exclusivement à des réponses à des chocs. 6% des positions nettes d'achats de CDS compensant des positions en dette demeurent non identifiées.

Enfin, les spéculateurs utilisent les CDS pour acquérir du risque de crédit, soit pour amplifier leurs expositions pré-existantes, soit pour obtenir une exposition au risque de crédit sans détenir la dette sous-jacente (on parle alors de spéculation à nu). La spéculation représente 73% des achats de CDS, tandis que pratiquement tous les vendeurs de CDS sont des spéculateurs. Nous constatons aussi que 95% des positions courtes en risque de crédit le sont via des CDS, car la stratégie équivalente via la dette, la vente de dette à découvert, peut être soumise à des frictions importantes.[9]

Étant donné que la vente de CDS correspond rarement à une stratégie de couverture ou d'arbitrage, presque tous les CDS vendus viennent en sus des EAD des vendeurs. L'effet total des échanges de CDS sur les EAD dépend alors uniquement de la part de spéculateurs parmi les acheteurs de CDS. Dans notre base de données, la prise en compte des CDS entraîne ainsi une augmentation des EAD vis-à-vis des entités référençant des CDS de 10 à 15%.

Le lien entre concentration et prise de position sur le marché des CDS dépend de la stratégie poursuivie. Dans un modèle de gestion des risques avec coûts fixes, Atkeson et al. (2015) prévoient logiquement que les investisseurs cherchent à couvrir en priorité leurs plus grandes expositions à la dette. En revanche, il existe plusieurs théories interrogeant les choix des spéculateurs. D'un côté, ces derniers pourraient souhaiter *substituer* la dette par des CDS dans un souci de partage des risques. De plus, comme les CDS ont des coûts de transaction plus faibles que la dette, les investisseurs peuvent choisir de manière optimale leur instrument préféré en fonction de leur profil de liquidité. Cependant, selon Che and Sethi (2014), les spéculateurs peuvent également profiter des exigences de marge plus faibles sur le marché des CDS et les utiliser pour amplifier leurs expositions via un levier synthétique plus élevé.

Il existe deux difficultés à surmonter pour identifier l'effet de la concentration des expositions sur l'utilisation de CDS. D'une part, l'introduction de CDS portant sur une entreprise

[8]Historiquement, c'est là l'origine de la création des CDS par J.P. Morgan : la banque voulut ouvrir une ligne de crédit de $5 Mds à Exxon suite au naufrage de l'Exxon Valdez en 1989, mais créa un CDS avec la Banque européenne pour la reconstruction et le développement pour ne pas avoir à porter tout le risque associé.

[9]La vente de dette à découvert nécessite de localiser des prêteurs de titres et de gérer le risque de ne pas trouver de vendeurs de titres à échéance (Duffie et al., 2002; Nashikkar et al., 2011).

peut influencer son comportement avec des conséquences sur la concentration des expositions et le niveau de risque du sous-jacent. Les études empiriques ont tendance à montrer que l'échange de CDS sur une entreprise permet à cette dernière d'émettre davantage de dette à des taux plus bas (Hirtle, 2009; Saretto and Tookes, 2013), ce qui aboutit à une hausse de son risque de défaut (Subrahmanyam et al., 2014). Nous restreignons notre analyse aux sous-jacents sur lesquels des CDS sont échangés, de sorte qu'ils aient a priori des incitations comparables à accroître leur endettement.

Le deuxième et principal défi est que les investisseurs choisissent potentiellement simultanément leurs expositions sur les deux marchés. Les investisseurs peuvent augmenter leur demande de dette en sachant qu'ils s'en délesteront partiellement sur le marché des CDS. Inversément, ils peuvent réduire leur demande de dette en choisissant plutôt de vendre les CDS correspondants. Pour surmonter ce problème, nous instrumentons la part de chaque exposition dette en portefeuille, par la part de la dette brute du sous-jacent dans l'univers des sous-jacents détenus par l'investisseur au cours de notre période d'observation. L'instrument suppose que les investisseurs répartissent au moins partiellement leurs avoirs en dette de manière proportionnelle entre entités de référence.

La résolution de ces deux problèmes d'identification est l'une des principales contributions de cet article, un progrès par rapport aux traditions théoriques (Atkeson et al., 2015) et empiriques (Oehmke and Zawadowski, 2017; Jiang et al., 2021) en vigueur, qui supposent que les expositions à la dette sont données lorsqu'on examine les effets des CDS.[10]

Conformément aux attentes, les banques et les dealers utilisent les CDS pour couvrir leurs expositions les plus concentrées. Pour les fonds, la concentration ne semble en revanche pas être un déterminant des stratégies de couverture. Cela pourrait être lié à une réglementation plus stricte de la concentration des expositions bancaires.[11] Les effets sont économiquement importants : pour chaque point de pourcentage (pp) supplémentaire de concentration de la dette, la probabilité de couvrir cette exposition augmente de près de 31 pp pour les banques et de 113 pp pour les dealers (à comparer aux concentrations médianes d'exposition à la dette s'élevant respectivement à 0,11 pp et 0,07 pp parmi les investisseurs utilisant potentiellement les CDS à des fins de couverture).

Concernant les spéculateurs vendeurs de CDS, nos résultats corroborent la thèse de Che and Sethi (2014) selon laquelle les investisseurs utilisent les CDS en complément de la dette. Conditionnellement à détenir une exposition dette, les investisseurs vendent davantage de CDS si cette exposition représente une plus grande proportion de leur portefeuille de dette.

[10] Cela repose généralement sur l'hypothèse selon laquelle la dette est moins liquide que les CDS.

[11] Par exemple, l'article 394 du CRR exige des banques qu'elles déclarent toutes leurs expositions dépassant le seuil de 10% de leur capital éligible, tandis que l'article 395 impose une limite stricte de concentration des expositions à 25% du capital éligible.

L'absence de résultats pour les dealers est cohérente avec leur rôle d'intermédiaires, leurs positions venant largement en miroir de celles de leurs contreparties. Les effets sont à nouveau économiquement significatifs : la probabilité de vendre des CDS en sus d'une détention de dette augmente de 6 pp pour les fonds et de 103 pp pour les banques pour chaque point de pourcentage supplémentaire de concentration des expositions dette (à comparer aux médianes de concentration d'exposition à la dette de respectivement 0,5 pp et 0,03 pp parmi les spéculateurs potentiels).

Par définition, les spéculateurs à nu échangent des CDS sur des expositions pour lesquelles ils n'ont aucune dette sous-jacente. Cependant, nous constatons également que les banques et les fonds d'investissement ont tendance à vendre davantage de CDS à nu sur des sous-jacents appartenant à des ensembles pays-notation de crédit qu'ils détiennent déjà en grande quantité, ce qui confirme une fois de plus les considérations de Che and Sethi (2014).

Dans la dernière partie de l'article, nous nous demandons si les CDS modifient la composition en risque de crédit de l'encours d'EAD. Il existe au moins quatre raisons pour lesquelles les incitations des investisseurs à échanger des CDS (par rapport à la dette) peuvent augmenter avec le risque du sous-jacent. Les désaccords sur les risques associés (Oehmke and Zawadowski, 2015) ou les incitations à la couverture Atkeson et al. (2015) peuvent tous deux être plus élevés pour les entreprises plus risquées. Les CDS peuvent également nécessiter des marges initiales moins importantes que des positions à levier similaires sur le marché de la dette, un avantage qui augmente avec le risque de référence (Darst and Refayet, 2018). Enfin, les avantages liés à l'opacité des transactions sur les marchés des produits dérivés pourraient augmenter avec le niveau de risque du sous-jacent (Jiang et al., 2021).

De même que pour la concentration, il existe des problèmes d'endogénéité car les positions en dette et CDS sont potentiellement déterminées conjointement. Les investisseurs échangeant des CDS peuvent réduire leurs investissements en dette risquée, étant donné que les CDS sont relativement attractifs pour ces niveaux de risque. Nous comparons le niveau de risque des portefeuilles de dette entre les investisseurs échangeant des CDS, et les investisseurs similaires n'en échangeant pas, et ne décelons pas de preuve de changement de prise de risque des investisseurs sur le marché de la dette au moment où ils entrent sur le marché des dérivés de crédit.

Pour un même investisseur, la probabilité d'échanger des CDS augmente avec le risque du sous-jacent, tel que mesuré par sa prime de CDS, pour toutes les stratégies et tous les secteurs. Ces résultats sont valables en contrôlant par la liquidité des obligations et des CDS. Nous trouvons également que les banques, les dealers, et dans une certaine mesure les fonds d'investissement, utilisent les CDS pour arbitrer les notations de crédit, c'est-à-dire acquérir davantage de CDS sur des sous-jacents affichant des primes élevées par rapport à leur note.

Ce comportement peut être motivé par des incitations en matière de communication ou de réglementation (Becker and Ivashina, 2015).

Dans l'ensemble, les CDS semblent avoir un effet ambigu sur la répartition du risque de crédit entre les investisseurs, même si le papier ne propose pas de cadre normatif. Les investisseurs utilisent les CDS pour couvrir leurs expositions les plus concentrées. Dans le même temps, l'échange de CDS augmente le montant total d'expositions au défaut, permet aux investisseurs d'augmenter leur exposition aux contreparties auxquelles ils sont déjà le plus exposés, et augmente le niveau de risque moyen de l'encours de risque de crédit en facilitant les échanges sur les sous-jacents les plus risqués.

Chapitre 3 : "Habitat sweet habitat" : les effets hétérogènes des programmes d'achat d'actifs de l'Eurosystème

La diversité croissante des programmes d'achats d'actifs et la flexibilité dont disposent les banques centrales pour les mettre en œuvre[12] suggèrent que tous les achats d'actifs ne sont pas équivalents. En particulier, le canal du rééquilibrage de portefeuille peut avoir des conséquences différentes en fonction du type d'investisseurs détenant initialement les titres visés. Intuitivement, l'achat de titres détenus par les banques peut soutenir la distribution de crédit, tandis que l'achat de titres détenus par des fonds d'investissement pourrait stimuler leur demande pour des titres non rachetés et éventuellement plus risqués.

L'un des cadres théoriques les plus répandus pour comprendre ce canal est la théorie des habitats préférés, introduite historiquement par Tobin (1965) et reformalisée plus récemment par Vayanos and Vila (2021). Comme l'a souligné Haruhiko Kuroda, ancien gouverneur de la Banque du Japon :

> La capacité des programmes d'achats d'actifs à grande échelle des banques centrales à parvenir à réduire les primes de terme repose sur la validité de l'hypothèse d'existence des habitats préférés.

Les achats d'actifs par les banques centrales réduisent l'encours actuel et attendu de risque de duration, de liquidité et de crédit dans l'économie, ce qui permet de diminuer le prix du risque sur le marché. La nature des titres rachetés revêt de l'importance dans la

[12] Par exemple, l'Eurosystème a décidé de s'autoriser à réinvestir de manière flexible les titres acquis dans le cadre du PEPP, ce qui témoigne de sa volonté de pouvoir soutenir les prix dans des segments de marché spécifiques. Voir : `https://www.ecb.europa.eu/press/pr/date/2021/html/ecb.mp211216~1b6d3a1fd8.en.html`.

mesure où chaque titre comporte un niveau de risque différent et entrainera donc une baisse spécifique des primes de risque.

La théorie de l'habitat préféré prévoit également que ces effets dépendront de la structure initiale de détention des titres achetés. Dans cette approche, la demande de titres est segmentée entre deux types d'investisseurs. Les "arbitrageurs" maximisent le couple moyenne-variance du rendement de leur portefeuille, et veillent à ce qu'une condition de non-arbitrage prévale entre les titres. A l'inverse, les investisseurs à "habitat préféré" sont spécialisés dans une classe d'actifs donnée, au sein de laquelle ils affichent une demande élastique. Cela fait apparaître deux canaux de transmission supplémentaires. Tout d'abord, les achats d'actifs ont des effets *locaux* sur les prix. La réduction de l'offre d'actifs au sein d'habitats préférés entraine une hausse du prix de ces actifs en sus de ce que prédirait la condition de non-arbitrage des arbitrageurs. Par exemple, les fonds ayant un mandat d'investissement pour des titres de dette souveraine de la zone euro peuvent être réticents à les vendre faute d'alternatives. Ensuite, la segmentation de la demande de titres permet l'activation du canal du rééquilibrage de portefeuille. À offre d'actifs constante, les variations de courbe des taux peuvent affecter la demande relative d'actifs. En présence de contraintes de bilan, les gains liés à la hausse des prix des actifs peuvent également affecter de manière disproportionnée certains secteurs et accroître leur demande d'actifs (Albertazzi et al., 2020). Enfin, et ce sera l'objet de ce papier, le changement de *composition* de l'offre d'actifs, conséquence de la substitution de titres de dette par des réserves de banque centrale, pourrait inciter à un rééquilibrage dès lors que les vendeurs d'actifs recomposent leur portefeuille optimal. Comme indiqué lors de l'annonce de l'assouplissement quantitatif par la Banque centrale européenne (BCE) :[13]

> La BCE achètera contre de la monnaie de banque centrale, sur le marché secondaire, des obligations émises par les administrations centrales, les agences et les institutions européennes de la zone euro. Les institutions vendant ces titres pourront l'utiliser pour acquérir d'autres actifs et octroyer des crédits à l'économie réelle.

Ce type de rééquilibrage est également stimulé par l'augmentation de l'offre d'actifs en circulation, qui survient soit mécaniquement lorsque la banque centrale achète des titres auprès d'institutions ne détenant pas de réserves (Christensen and Krogstrup, 2016), soit indirectement via une augmentation des émissions par les agents privés (voir par exemple Abidi and Miquel-Flores (2018) ou Todorov (2020) qui montrent comment le programme d'achat d'obligations d'entreprises (CSPP) a stimulé les émissions obligataires). Ce canal du

[13]Voir: `https://www.ecb.europa.eu/press/pr/date/2015/html/pr150122_1.en.html`.

rééquilibrage de portefeuille induit par l'augmentation des réserves en circulation sera l'objet de cette étude.

Dans cet article, nous montrons que différents types d'investisseurs rééquilibreront leur portefeuille de manière différente après avoir vendu leurs titres à l'Eurosystème. Idéalement, nous souhaiterions comparer le rééquilibrage de deux investisseurs aux profils différents au moment où ils se délestent du même titre. Cependant, les achats de tous types de titres sont simultanés et il semble difficile de distinguer l'effet des différents types de ventes. Par conséquent, nous procédons en deux étapes, en exploitant les caractéristiques spécifiques de l'assouplissement quantitatif en zone euro. Tout d'abord, nous identifions les contreparties des achats effectués par l'Eurosystème et estimons leurs élasticités relatives en fonction de la nature du titre acheté. Ensuite, nous estimons comment chaque type d'investisseur rééquilibre son portefeuille lorsqu'il vend ses titres à l'Eurosystème.

La première partie de l'article s'appuie sur la diversité des programmes d'achats d'actifs mis en œuvre dans la zone euro pour identifier les contreparties des achats de l'Eurosystème en fonction du type de titre acheté. Pour ce faire, nous avons constitué une base de données comportant toutes les détentions de titres par secteur d'investissement, appariée aux achats d'actifs de l'Eurosystème au titre de quatre programmes différents de 2014T4 à 2020T4 : le troisième volet du programme d'achat d'obligations bancaires sécurisées (CBPP3), celui de titres souverains (PSPP), celui d'obligations d'entreprises (CSPP) et celui associé à la pandémie recoupant tous les périmètres d'éligibilité précédents et les élargissant dans certaines directions (PEPP). Nous identifions les contreparties à ces achats en fonction de deux caractéristiques des titres : leur classe d'actifs - ce qui nous permet d'évaluer l'impact des différents programmes d'achat - et leur maturité résiduelle. Nous comparons les variations de détention de titres achetés à celles de titres similaires non achetés, pour les trois principaux secteurs de détention de la zone euro : les banques, les fonds d'investissement et les compagnies d'assurance et fonds de pension. En identifiant ceux qui vendent une plus grande part de leurs détentions à l'Eurosystème et en contrôlant par la demande sectorielle pour les titres éligibles, nous sommes en mesure de classer les élasticités des différents secteurs pour chaque type de titre acheté. À notre connaissance, nous sommes les premiers à estimer explicitement les élasticités relatives aux différents types d'achats grâce à notre accès exclusif aux données d'achat titre à titre pour quatre programmes différents.

Nous constatons que les banques sont les investisseurs de la zone euro les plus élastiques aux rachats d'obligations souveraines et sécurisées, tandis qu'elles affichent une élasticité comparable à celle des fonds pour les obligations d'entreprises. En raison de leur part de marché importante dans le premier cas, les banques se retrouvent être les principales contreparties aux rachats de zone euro pour les programmes CBPP3, PSPP et PEPP, tandis que

les fonds d'investissement fournissent l'essentiel des titres rachetés dans le cadre du CSPP. Les assureurs semblent être aussi élastiques que les fonds pour les obligations souveraines et sécurisées, et moins élastiques que les fonds et les banques pour les obligations d'entreprises.

En ce qui concerne les maturités résiduelles, les différences entre secteurs s'accentuent à mesure que la maturité augmente, et les banques semblent être les seules vendeuses de titres de maturité résiduelle supérieure à 15 ans. L'élasticité (par rapport aux autres secteurs) des assureurs diminue avec la maturité, tandis que celle des fonds atteint un pic pour les échéances intermédiaires. Une explication à cette hétérogénéité est à nouveau l'existence d'habitats de maturité différents. L'autre hypothèse est que les achats d'actifs modifient les préférences de maturité des investisseurs. Nous utilisons des données au niveau investisseur pour dissocier ces deux effets, en supposant que la maturité préférée de chaque investisseur corresponde à la maturité moyenne des titres qu'il détenait avant le début de l'assouplissement quantitatif. Le comportement des fonds se trouve en effet être celui qu'on attendrait de la part d'investisseurs à habitat préféré. Les fonds apparaissent plus élastiques aux achats de titres les plus éloignés de leur mandat. Les fonds sont en effet soumis à à une forme plus stricte d'habitat - le mandat d'investissement. De leur côté, les assureurs semblent orienter leurs portefeuilles vers des échéances plus longues à mesure qu'ils vendent, ce qui témoigne d'un comportement de recherche de maturité.

Dans la deuxième partie de l'article, nous estimons comment différents types d'investisseurs rééquilibrent leur portefeuille lorsqu'ils vendent à l'Eurosystème. Cela revient à se focaliser sur le canal du rééquilibrage de portefeuille induit par l'introduction de liquidité - identifiée ici comme la vente de titres. Bien que le rééquilibrage de portefeuille puisse également être induit par d'autres motifs tels que les gains liés à la hausse des prix des actifs, notre objectif est de déterminer si l'identité des détenteurs des titres achetés importe. Les investisseurs détenant les titres achetés sont directement affectés par l'injection de liquidité, tandis que les hausses de prix des actifs peuvent affecter tous les investisseurs indépendamment du choix d'actifs effectivement achetés (et peuvent d'ailleurs survenir sans achat d'actifs par le simple guidage des anticipations).

Pour ce faire, nous construisons une mesure directe de vente de titre par investisseur, que nous relions à la croissance des avoirs par investisseur et titre. Bien que les ventes d'actifs de chaque investisseur ne soit pas directement observable, nous imputons ce montant à partir des variations de détentions de titres achetés concomitantes aux rachats effectifs de titres, à fréquence trimestrielle. Notre identification repose sur trois caractéristiques clé.

Premièrement, l'estimation des changements de demande associés aux ventes d'actifs est sujette aux biais de variable omise et de causalité inversée. Concernant les variables omises, d'autres chocs que l'assouplissement quantitatif peuvent entraîner une corrélation

entre notre mesure de vente d'actifs, et les changements de demande. Par exemple, un fonds d'investissement subissant des rachats de parts pourrait chercher à réduire ses avoirs, y compris ses avoirs de titres simultanément par l'Eurosystème, ce qui donnerait l'impression que c'est la banque centrale qui a conduit ce fonds à réduire ses avoirs. Le problème de causalité inversée provient de ce que les investisseurs cherchant à réduire la taille de leur portefeuille pourraient avoir tendance à proposer leurs actifs à l'Eurosystème, qui pourrait à son tour acheter de manière disproportionnée auprès d'investisseurs en difficulté.[14] Pour contourner cette endogénéité, nous instrumentons la vente d'actifs d'un investisseur par son exposition aux actifs éligibles au rachat dans la période immédiatement précédente, comme proposé par Rodnyansky and Darmouni (2017) ou Koetter (2020).

Une autre préoccupation est que les investisseurs exposés aux achats de l'Eurosystème sont de manière disproportionnée exposés aux augmentations potentielles d'émissions qui en découlent. Nous exploitons la granularité de notre base de données qui nous permet d'introduire par des effets fixes ISIN-trimestre, qui absorbent ainsi tout choc d'offre d'actifs, dans l'esprit de Khwaja and Mian (2008).

Enfin, un problème plus général est que l'exposition aux achats de la banque centrale peut être corrélée à d'autres chocs spécifiques à chaque investisseur qui pourraient affecter sa demande d'actifs. Par conséquent, pour chaque secteur, nous contrôlons pour un nombre (différent) de caractéristiques de bilan qui pourraient effectivement influencer sa demande d'actifs.

On distingue différents schémas de rééquilibrage en fonction du secteur considéré. Les assureurs augmentent marginalement leur demande pour des titres de créance non libellés en euros, bien que notre instrument soit faible en raison de la variabilité plus limitée de leurs ventes d'actifs. Parmi les fonds d'investissement, les mandats d'investissement semblent dicter l'ampleur du rééquilibrage. Les fonds obligataires ont tendance à substituer les titres vendus par des titres de créance similaires. En revanche, les fonds diversifiés ont tendance à augmenter leur demande pour les actions, ainsi que pour les titres de créance non libellés en euros. Pour terminer, les banques ne semblent pas modifier leur demande de titres. En revanche, nous montrons que les banques qui vendent à l'Eurosystème ont bien augmenté leurs crédits aux entreprises entre 2019 et 2020.

Les achats de titres n'ont donc pas le même effet sur la demande selon la nature de la contrepartie. Les implications de ce résultat sont importantes pour la conception des programmes d'achats d'actifs des banques centrales. Les banques centrales doivent non seulement décider de la quantité de risque à retirer du marché, mais aussi identifier ses

[14]En pratique, la banque centrale implémente tous ses rachats via des dealers, mais les contreparties finales seraient dans ce cas ces investisseurs en difficulté.

contreparties potentielles. L'achat d'actifs appartenant principalement aux banques commerciales (comme lors du CBPP3 ou du PSPP, ou lors de l'achat de titres à plus long terme) stimulera le crédit bancaire. Au contraire, acheter des titres détenus par des fonds d'investissement (comme lors du CSPP ou de l'achat de titres à plus court terme) amplifiera le rééquilibrage vers des actifs plus risqués si les fonds vendeurs disposent de mandats d'investissement flexibles comme les fonds diversifiés français.

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